# Enhancing Emergency Response in Short-notice Bushfire Evacuation

A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

by

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## Declaration

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; any editorial work, paid or unpaid, carried out by a third party is acknowledged; and, ethics procedures and guidelines have been followed.

Shahrooz Shahparvari
October, 2016

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# Dedication

I dedicate this thesis to the memory of my beloved grandfather for his endless support and encouragement.

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## Acronyms

| | |
|---|---|
| **MOP** | Multi-Objective Programming |
| **MILP** | Mixed-integer Linear Programming |
| **MIMOLP** | Mixed-integer Multi Objective Linear Programming |
| **CMDVRP-TW** | Deterministic Vehicle Routing Problem |
| **P-CMDVRP-TW** | Possibilistic Vehicle Routing Problem |
| **LEBMD-TW** | Late Evacuation Bushfire to Multiple Destinations with Time Windows |
| **CMDVRP-TW** | Capacitated Multiple Destination Vehicle Routing Problem with Time Window |
| **P-CMDVRP-TW** | Possibilistic Capacitated Multiple Destination Vehicle Routing Problem with Time Window |
| **OF** | Objective Function |
| **GA** | Genetic Algorithm |
| **RPD** | Related Percentage of Deviation |
| **SCM** | Supply Chain Management |
| **SC** | Scenario |
| **DM** | Decision Maker |
| **MCDM** | Multi Criteria Decision Making |
| **BCRC** | Bushfire Cooperative Research Centre |
| **TH method** | Torabi Hassini approach |
| **LH method** | Lai and Hwang's augmented max–min approach |
| **MW method** | Extended Werners |
| **LZL method** | Two-phase Method |
| **NIS** | Negative ideal solution |
| **PIS** | Positive Ideal Solution |
| **RHS** | Right hand side |
| **LHS** | Left hand side |
| **CFA** | Country Fire Authority |
| **AFAC** | Australasian Fire and Emergency Service Authorities Council |
| **VBRC** | Victorian Bushfires Royal Commission |
| **P.A.S** | Prepare, Act, and Survive |
| **VFBV** | Volunteer Fire Brigades Victoria |
| **NP-hard** | Nondeterministic Polynomial time |

# Abstract

A bushfire, or a wildfire, is a freely burning, uncontrolled and unplanned fire in regional and rural areas. The impacts of bushfire range from destruction of properties and critical infrastructure, supply chain disruptions, to psychological damage, injuries and fatalities of people and wildlife. In the USA, for example, there are 60,000 to 80,000 wildfires burning 3 to 10 million acres of land, causing 4,000 fatalities and 20,000 injuries each year. The Fort McMurray 2016 bushfire in Canada destroyed approximately 2,400 buildings and resulted in evacuation of 80,000 people and the estimated wildfire insurance payouts are around CAD$9 billion. In Russia, the total cost of damage from bushfires in 2010 was about USD$15 billion in addition to 55,526 casualties caused by bushfire heat waves.

In Australia, bushfires have claimed hundreds of lives and resulted in billions of dollars of damage. In Victoria alone over the last few decades, 300 people have lost their lives and 4,185 have suffered serious injuries. 32 per cent of all bushfire fatalities in Australian history (176 out of 552 deaths) were associated with short-notice evacuation. The more recent 2009 Black Saturday bushfires resulted in 173 deaths, displacement of more than 7,500 residents, and caused $4.5 billion dollars in financial losses. Notably, over 50 per cent of those who were evacuated on the Black Saturday were last-minute evacuees.

Short-notice bushfire evacuation is a complex, dynamic and multifaceted problem. Complexity in evacuation emanates due to multi-stage process, which necessitates operational decisions and actions to be simultaneously performed. Time-sensitive decisions in bushfire evacuation therefore entail assigning and allocating evacuees to secured shelters, selecting suitable vehicles and choosing optimal yet low-risk routes. Uncertainties in time-windows, network disruptions and bushfire propagation make the evacuation problem more dynamic and multifaceted. Any operational planning failure could adversely affect the efficiency and effectiveness of disaster response and hence could increase the risk of human injuries or fatalities. Emergency services agencies therefore require a robust decision support tool that enables simultaneous processing of complex decisions to help minimise risk and cost.

This thesis develops multi-objective optimisation models to enhance emergency response and operational planning during a short-notice bushfire evacuation. Four key interrelated research questions are answered as follows: What optimisation approaches can be used to maximise short-notice evacuation under a given set of bushfire scenarios?; What is the optimum allocation of shelters required to maximise spatial coverage of late evacuees in bushfire affected area?; How can the most efficient routes (i.e. safest and shortest) be determined to transfer people from assembly points to designated shelters?; How can vehicle assignment and scheduling be optimised to maximise short notice evacuation within a specified time window?

Three key optimisation models are developed to compute solutions to shelter allocation, vehicle assignment and routing problems with time window constraints and disruption scenarios under conditions of uncertainty. (I) The *Late Evacuation during Bushfire to Multiple Destinations with Time Windows* (LEBMD-TW) is a mixed-integer multi-objective optimisation model. The Ɛ-constraint method is applied as the solution approach. (II) The *Capacitated Multiple Destination Vehicle Routing Problem with Time Window* (CMDVRP-TW) is a novel vehicle routing problem- model integrating several VRP variants. A heuristic solution approach is developed to tackle complex vehicle routing problem. The effectiveness of proposed heuristic algorithm is evaluated by comparison with a Meta-heuristic genetic algorithm using set of various computational experiments. Finally, (III) *Possibilistic Capacitated Multiple Destination Vehicle Routing Problem with Time Window* (P-CMDVRP-TW) is presented as the key contribution of this thesis because of the novelty of integrating the CMDVRP-TW model with fuzzy set theory concepts.

These optimisation models are pilot tested in a small numerical experiment in Lake Eildon Park in Victoria, Australia. A real case study context is then presented using the 2009 Black Saturday bushfires in Victoria. Three plausible bushfire scenarios are considered. The *baseline scenario* represents the propagation of actual bushfires. The *minor disruption scenario* incorporates shutting down of a high-capacity shelter, whilst the *major disruption scenario* disconnects a shelter and cut off the main arterial road from evacuation networks.

The models generated shortest and safest routes to transfer late evacuees from bushfire-affected areas within the set time windows, taking into account road accessibility and available resources. The LEBMD-TW model efficiently assigned available shelters to absorb all 1,100 late evacuees transferred from assembly points in the bushfire affected areas by a fleet of five buses and twelve vans. The CMDVRP-TW model suggests the evacuation of late evacuees by seven rescue vehicles in four shelters is feasible. A decrease in the number of assigned vehicles is possible, however, it increases the risk of transporting evacuees via high risk routes. The P-CMDVRP-TW model generated optimal routes and evacuation solutions under uncertainty and hard constraints. It was possible to evacuate equal numbers of evacuees by using only six buses and four shelters under low disruption risk. The P-CMDVRP-TW model under disruption scenarios generated an evacuation plan to transfer all late evacuees with seven buses and four shelters.

The computed solutions demonstrate that short-notice evacuation is manageable with advanced operational planning. The models are useful in the development of emergency plans and evacuation strategies to enhance rapid response to last-minute evacuation in a bushfire emergency. There are four key implications for short-notice evacuation planning, (1) the capacity and capability of emergency services agencies would be enhanced to identify optimal allocation of shelter to transfer evacuees under any emergency evacuation scenarios; (2) rescue vehicles required to optimise the spatial coverage would be effectively determined; (3) emergency vehicles would be instantaneously scheduled which would lead to an improved efficiency and effectiveness of emergency response; and (4) a comprehensive transit plan can be developed using mapping of routes to mitigate potential risks for each road link in the network. Considering shadow evacuation and background traffic as a key caveat to the emergency evacuation modelling could be an interesting future study as well. With appropriate model calibration and adjustment, this modelling approach could also be applied to other disasters such as flooding and cyclones, which are also widely prevalent in Australia and other countries.

## Chapter 1

# Introduction

## 1.1 Introduction

A wildfire, commonly known as bushfire in Australia, is a freely burning, uncontrolled and unplanned fire, which often occur in rural and regional areas (CFA Definitions, 2012). Bushfires are generally considered as a natural hazard but it is also associated with arsons with malicious intent (Willis and Christensen, 2004). Every year, bushfires result in catastrophic economic and human losses (Butry et al., 2001). Bushfires pose a constant threat to regional communities, particularly those living in bushfire-prone areas.

In recent decades, there has been a substantial increase in the number and intensity of bushfires around the world (Cameron et al., 2009). Global warming and climate change have potentially increased the risk of bushfire, particularly in extreme summer season in many countries including Australia (Teague et al., 2009), USA (Westerling et al., 2006), Canada (Podur et al., 2002) and Russia (Kharuk et al., 2007). The intensity and directionality of bushfire propagation are influenced by various environmental factors such as the accumulation of combustible materials, extreme temperature, wind speed and topographic characteristics such as slope and aspect. Bushfire propagation rate can double with every 10 degree increase in slope (Whittaker et al., 2009) and with a small change in wind speed (Whittaker et al., 2009). During a bushfire, temperature can reach 800 degree Celsius (Volunteer Fire Brigades Victoria (VFBV), 2013) and the height of the flame crown can reach as high as 30 meters (Victorian Bushfires Royal Commission, 2010).

Bushfires are an inherent characteristic of Australia's environment. Bushfires are widespread and occur frequently. They damage and destroy houses, farms, crops, livestock and infrastructure such as roads and rail (Teague et al., 2009). More than 40 per cent of Australian land contains combustible materials, which provide a favourable condition for bushfire ignition. In addition, arid and dry climate, coupled with high temperature and strong winds elevate the risk of bushfires in Australia (Victorian Bushfires Royal Commission, 2010). As of 1999, several major fires have affected Australia including the 2003 Canberra fire (four deaths, more than 100 people injured and around 500 homes lost), the 2006 Eyre Peninsular fires (nine deaths and 110 people injured) and the 2009 Victorian bushfires (173 deaths and more than 2000 homes lost).

In the past 150 years, approximately half of the bushfire related economic losses in Australia occurred in the state of Victoria, which represents only about 3 per cent of the total land mass of Australia (Luke and McArthur, 1978). Besides the financial cost of A$2.5 billion, significant losses of life have also occurred with more than 300 deaths and 4,185 injuries occurring in Victoria since the early the 20th century until 2009. Victoria accounts for 39 per cent of deaths and 57 per cent of the injuries from all the major Australian natural disasters in that period (Krusel and Petris, 1992).

In bushfires, the decision to stay or leave early is critical for community safety. Communities at risk may decide to leave early, or take shelter-in-home or shelter-in-refuge (Cova et al., 2011). Arguably, an early evacuation is the safest option to protect life (Cova et al., 2009), nonetheless most people prefer to stay and protect their properties. Furthermore, many of them leave at the last minute (Victorian Bushfires Royal Commission, 2010), which significantly exacerbates the risk of injury or death. Late evacuation also exposes evacuees to radiant heat, which is identified as one of the main reasons for human fatalities (Teague et al., 2009). For example, in the 2009 Black Saturday bushfires in Victoria, Australia, 119 out of 173 fatalities (68 per cent) died as a result of late evacuation (Victorian Bushfires Royal Commission, 2010).

Currently, the Australian evacuation policy, *Prepare Act and Survive* (Country Fire Authority, 2011), "P.A.S" permits people to decide to leave early or stay until the last minute. Due to the provision of late evacuation coupled with the uncertainty of rapid propagation of bushfire, the necessity of developing comprehensive evacuation plans to enhance evacuation response in emergency situations is undeniably critical. Hence, the major challenge in designing an evacuation plan is to evacuate people from bushfire-prone areas to safe areas using the safest and shortest routes within a restricted time window.

As a bushfire spreads, it disrupts emergency supplies and transportation networks. This in turn makes the evacuation of late evacuees more difficult. Road disruption within a dynamic bushfire context can increase the complexity of evacuation and delay the emergency response. Under such situations, the development of an evacuation system requires a robust modelling capability that considers multiple objectives and constraints to reflect plausible bushfire scenarios.

There is, therfore, a need to develop a multi-objective optimisation model to enhance emergency response in the case of bushfires. It is vital to determine the optimal placement of shelters and the optimal and alternative ‘egress’ routes considering the number of evacuees in each area. This research will be the first study in Australia that models short-notice bushfire evacuation under various transportation network disruptions across different time windows. This research will develop appropriate emergency plans to increase the capacity of emergency services agencies in operational and strategic planning.

## 1.2 Aims and questions

This thesis aims to develop optimisation models to enhance the emergency response to short-notice bushfire emergency evacuation under different disruption scenarios.
To achieve this aim, four key research questions are addressed:

*RQ1:* What optimisation approaches can be used to maximise short-notice evacuation under a given set of bushfire scenarios?

*RQ2:* What is the optimum allocation of shelters required to maximise spatial coverage of late evacuees in bushfire affected area?

*RQ3:* How can the most efficient routes (i.e. safest and shortest) be determined to transfer people from assembly points to designated shelters?

*RQ4*: How can vehicle assignment and scheduling be optimised to maximise short notice evacuation within a specified time window?

## 1.3 Rationale for the research

Bushfire is a significant threat to regional communities in Australia, particularly those who live in bushfire-prone areas. Because bushfires in Australia have become a recurrent and seasonal phenomenon, bushfire risk is rising and the costs of bushfires related disasters are mounting (Teague et al., 2009). This poses significant planning challenges for emergency services agencies to respond efficiently and effectively to bushfire threats. Although direct and indirect costs are difficult to estimate, there are three cost components which show the scale of impact of bushfire on regional communtieis. These include loss of human life and injury; economic costs; and damage to ecosystems. These are discussed below.

### 1.3.1 Bushfire risk and the climate change

Bushfire risk in Australia is excessively high. In the past several decades, there has been a sharp increase in the number of bushfire events (Cameron et al., 2009). Climatic change and global warming and Australia's vegetation types have all aggravated the risk of bushfire occurrence (Victorian Bushfires Royal Commission, 2010). Bushfires in the past had generally been confined to the northern part of Australia, which has a tropical climate. Since 1910, however, there has been a two-degree increase in average temperature of Australia (Figure 1.2). Recently, due to climatic change and global warming, bushfires have started to shift towards the south of Australia which is the most populated area in the continent (Bowerman et al., 1995).

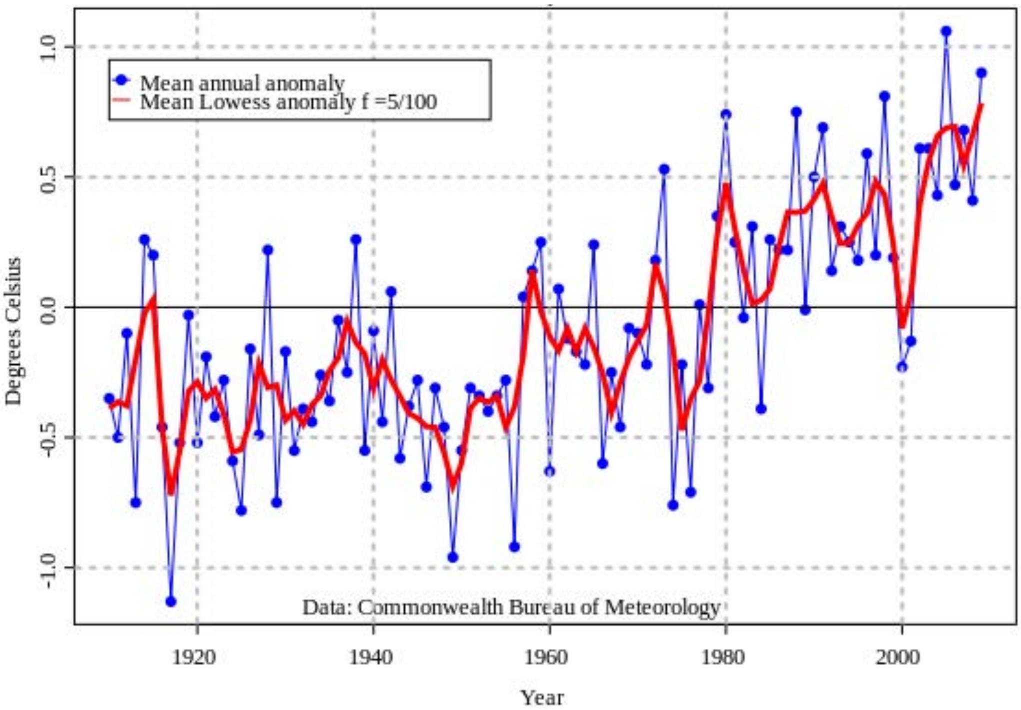



Figure 1.1 Australian average temperatures anomalies 1910-2009 (source: Common

wealth Bureau of Meteorology).

Referring to historical data, every two or three years a severe bushfire has occurred in Victoria, Australia which has caused severe losses.

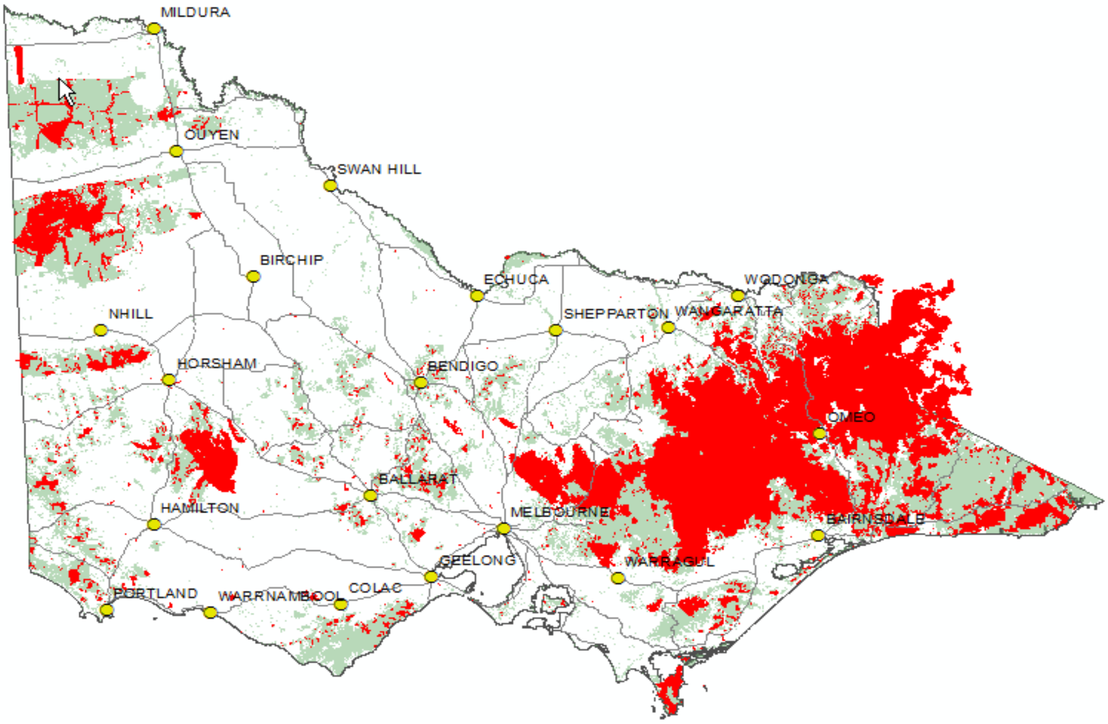



Figure 1.2 Extent of bushfires in the last 10 years in Victoria State, Australia (source: The State of Victoria Department of Sustainability and Environment 2009)

### 1.3.2 Social and economic loses

Bushfires can cause severe social and economic losses. In the comparison to bushfire losses in the world rankings, the 2009 Black Saturday Bushfires in Victoria is considered as one of the top ten deadliest bushfire/wildfire events in world history (Cameron et al., 2009) (see Table 1.1).

Table 1.1 Top eight bushfire incidents (source: Cameron et al. (2009))

| Rank | Location | Country | Year | Deaths |
|---|---|---|---|---|
| 1 | Peshtigo, Wisconsin | USA | 1871 | 1200 |
| 2 | Cloquet, Minnesota | USA | 1918 | 453 |
| 3 | Hinckley, Minnesota | USA | 1894 | 418 |
| 4 | Thumb region, Michigan | USA | 1881 | 300 |
| 5 | Matheson, Ontario | Canada | 1916 | 282 |
| 6 | Sumatra and Kalimantan | Indonesia | 1997 | 250 |
| 7 | Landes region | France | 1949 | 230 |
| 8 | Greater Hinggan | China | 1987 | 213 |
| 9 | Victoria | Australia | 2009 | 173 |

| | | | | |
|---|---|---|---|---|
| **10** | Miramichi, New Brunswick | Canada | 1825 | 160 |

In Australia, the State of Victoria is ranked first both in the number of fatalities and house destruction. More than 52 per cent of house losses and 72 per cent of fatalities, as a result of bushfires in Australia, have occurred in Victoria. Table 1.2 shows that there were 14,000 houses destroyed and 689 fatalities occurred.

Table 1.2 Australian bushfire losses since 1900 by State (source: McAneney et al. (2007))

| | **Bushfire incidents** | | **Houses destruction** | | **Fatalities** | |
|---|---|---|---|---|---|---|
| **State** | **Count** | **Percentage** | **Counts** | **Percentage** | **Count** | **Percentage** |
| **VIC** | 209 | 26% | 7355 | 52% | +500 | 72.5% |
| **NSW** | 407 | 52% | 2388 | 17% | 91 | 13.% |
| **TAS** | 20 | 3% | 1646 | 12% | - | 0% |
| **ACT** | 4 | 1% | 1178 | 8% | 12 | 2% |
| **SA** | 53 | 6% | 1103 | 8% | 50 | 7% |
| **WA** | 57 | 7% | 407 | 3% | 15 | 2% |
| **QLD** | 37 | 5% | 33 | 0.1% | 21 | 3% |
| **Total** | 787 | 100% | 14110 | 100% | 689 | 100% |

Figure 1.1 shows the increase in the number of bushfires in Victoria in recent years. Also the trend line (dashed blue line), indicates an increase both in area burnt and in the number of bushfires.

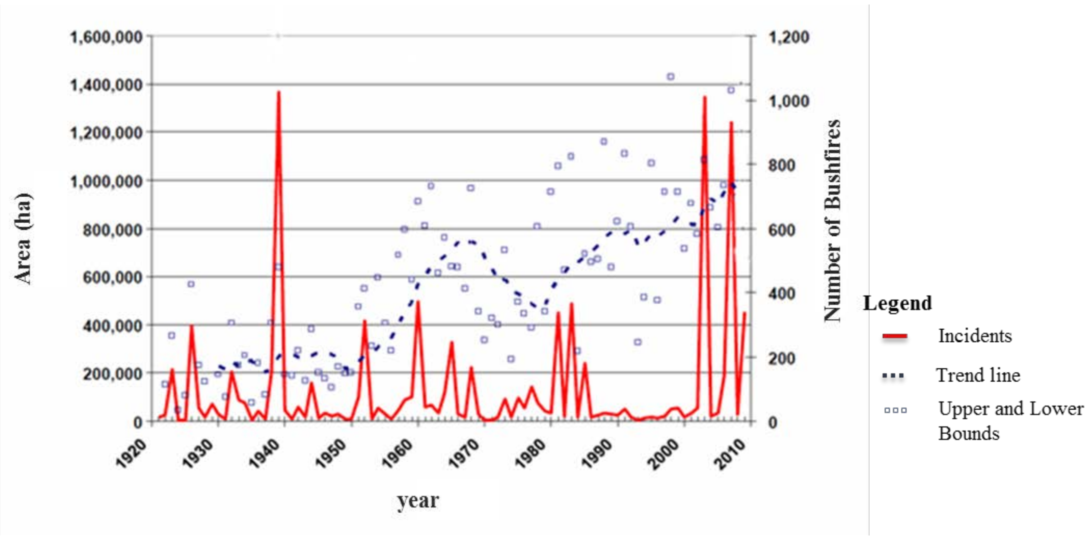



Figure 1.3 Number of bushfires in Victoria State 1920-2010 (source: Bryant (2010))

During the period of 1967 and 1999, bushfires in Australia had cost $2.5 billion (The Bureau of Transport and Economics Report, 2001). This corresponds to an average of 7 per cent of the total budget, spent on managing all major natural disasters in Australia during that period. Over the same period, 223 people died, which accounts for 39 per cent of total fatalities in all natural disasters in Australia. In the 2009 Black Saturday bushfires, besides $ 4.4 billion losses, 173 people died. This figure excludes the amount of $645 million compensation paid for 173 lives lost. This amount also did not include any assessment of the cost of the injuries received (Victorian Bushfires Royal Commission, 2010). Bushfires therefore are a major problem which consumes significant amount of funding to emergency planning and operational response.

### 1.3.3 Bushfire behaviour complexity

Bushfire propagation, including the intensity, directionality and geographic magnitude, is not easy to predict (Stepanov and Smith, 2012). The spatio-temporal dynamics of bushfire propagation is considerably complex. A rapid response and rescue actions need to be performed within a tight clearance time (Whittaker et al., 2013). Most of bushfire spread models are based on intensive empirical observations of the historical bushfire behaviour. However, any small variation in one of the key elements of bushfire propagation components (fuel, topography and weather condition) could drastically change the spread behaviour. For example, sudden change in the wind direction in the 2009 Black Saturday bushfires forced 7,562 Victorian citizens to be displaced within just 24 hours (Teague et al., 2009). Thus, time sensitivity and resource limitation are recognised to be major problems in the evacuation process of late evacuees.

## *1.4 Problem statement*

Efficient scheduling and routing of available vehicles for transferring people from the affected area to safe functioning shelters via the safest routes within the tight time windows is challenging. In bushfire situations, time and resources are often limited and the rescue time could vary from minutes to hours or days to transfer stranded evacuees to safer places. Due to the uncertainties associated with short-notice evacuation especially the spread of bushfire, quick response in minimum time is vital to save lives (Church and Sexton, 2002).

### 1.4.1 Decision making behavioural uncertainty

During bushfires, the decision to evacuate the area must be made before the emergence of the actual fire event (Victorian Bushfires Royal Commission, 2010). Often, the number of people evacuating early in bushfire is substantially less than other disasters such as floods and cyclones (Haynes et al., 2010). Most people do not make a decision to leave their properties until they make sure they are really threatened by bushfire (Southworth, 1991). Therefore, most people do not make timely decisions to leave early, shelter in home, or shelter in a refuge, what Cova (2011) referred to as protective actions. Early evacuation is indeed the safest approach to save lives against a bushfire threat (Cova et al., 2009). Yet, some people decide to stay and protect their properties regardless of the prevailing threat. The decision to evacuate is often too late. Late bushfire evacuation has been reported as the worst and most dangerous decision, which could culminate to severe injury and fatality (Victorian Bushfires Royal Commission, 2010).

### 1.4.2 Operational complexity

In case of a bushfire, evacuation warnings are often broadcasted to help guide people to assemble at designated sites, which are relatively safe and easily accessible. People are then transferred to safer shelters via organised rescue vehicles. However, due to the capacitated vehicle service rate (i.e. vehicle's capacity in transferring people), late evacuees assembling at assembly points may not be able to immediately board a rescue vehicle as it may not be available or over-utilised, leading to longer waiting times. This in turn further exposes people to a hazardous high-risk environment.

The bushfire context is complex, dynamic and multi-faceted. Evacuation is subject to stringent time constraints, and affected by potential disruption of facility or supply network. The complexity also increases due to the uncertainty of bushfire propagation. Shelters and roads may not remain available and accessible which require proper routing and scheduling. There is no exact procedure for emergency responses as it depends on the situated context within which the emergency occurs. Usually, the emergency services agencies (e.g., the police and CFA) will first evaluate the situation and assess the availability of operating shelters before the commencement of evacuees' transfer to safe shelters. Furthermore, bushfire emergency services agencies prefer to transport late evacuees to the closest functioning shelters before the bushfire reaches to assembly points via the available road network. This objective function necessitates applying advanced modelling to solve the complex evacuation problem. Depending on the length of trip time between an assembly point and the designated shelter via safest route, the emergency services agencies then assess the number of required rescue vehicles to transport late evacuees. In order to simulate a realistic bushfire evacuation situation, rescue vehicles are assumed to be capacitated to carry a finite number of evacuees on each trip (An et al., 2013). In addition, since each shelter is expected to serve the maximum number of late evacuees, it is assumed that each rescue vehicle will travel between assembly points and the designated shelters for additional boarding after alighting evacuees at shelters outside the bushfire affected area (Shahparvari et al., 2016a, An et al., 2013). This is seen as a major operational challenge as it requires optimising multitude of objectives functions under uncertainty.

### 1.4.3 Policy dilemma

After the investigation of the Ash Wednesday Bushfire (16 Feb 1983) and other bushfires over the last few years, the Parliament of the Commonwealth of Australia legislated the "*Stay or Go*" policy [colloquially known as "*Prepare, Stay and Defend or Leave Early*" (P.S.D.L.E)] in Australia in 2003 (Rhodes and Handmer, 2008). Under the "*Stay or Go*" policy, Australian fire agencies permitted residents to prepare, stay and defend their properties against bushfire or evacuate early. Late and mass evacuation however is considered to be a high-risk option. These recommendations were based on evidence that some households can defend their properties if they physically and mentally are prepared and willing to stay back (Victorian Bushfires Royal Commission, 2010). Furthermore, there no detailed evacuation routing plans that consider transferring late evacuees. This Stay & Go policy, however, was in contrast to the mandatory evacuation order which requires compulsory evacuation of residents from high risk areas (Australasian Fire Authorities Council, 2010).

The permit to stay and defend therefore contributed to the death of 113 people found inside their homes in the Black Saturday bushfires. Successive investigation of the causalities expressed that around 70 per cent had been sheltering at home when they perished (Handmer et al., 2010). The Victorian Bushfires Royal Commission (VBRC) [1]was then established to investigate the reasons of large scale fatalities. The

[1] "The 2009 Victorian Bushfires Royal Commission is an Australian Royal Commission conducted an extensive investigation into the causes of, the preparation for, the response to and the impact of the fires that burned throughout Victoria in late January and February 2009".

Commission found the un-organised late evacuation and road disruption might be associated with human losses.

After a comprehensive investigation, the VBRC made 67 policy amendment recommendations in its final report to the Victorian Government on 31 July 2010 (Teague et al., 2009). Among them is the development of an emergency bushfire evacuation plan including resource allocation and shelter assignment. It is vital to systematically and strategically plan how many shelters need be established and how the available routes are identified and used to evacuate late evacuees. These VBRC recommendations are now the key elements embedded in the recently announced national evacuation policy, called *Prepare. Act. Survive.* (P.A.S) (Australasian Fire Authorities Council, 2010). Despite this policy response, the execution of late evacuation plans remains problematic and challenging due to logistics complexity, multi-institutional coordination, environmental instability and uncertainty. The task of transferring evacuees from bushfire affected areas to safe shelters within a short notice time window through safe routes therefore continues to pose numerous operational challenges for emergency services agencies. The emergency response to a bushfire disaster becomes more difficult when the resources are finite and the relief supply chains are vulnerable to disruption.

### 1.4.4 Uncertainty in parameters

Short-notice evacuation requires careful consideration of multiple factors such as the number of evacuees at different locations within the region, availability of transit routes, the capacity of shelters and scheduling of number of available vehicles. Most of these parameters are unknown or are uncertain. It may be difficult to frame the problem parameters as exact values, due to insufficient historical data (e.g., no data on evacuees' population) or potential road disruptions. In addition, real-time fire behaviour data and probability distributions are often difficult to estimate, which in turn affect the reliability of modelling outputs. In addition, time window calculations (clearance time) for each town tend to be difficult to model deterministically. Instead, they should be represented by interval ranges (e.g., clearance time between 20-25 minutes). In addition, travel time from designated assembly points to safe shelters may often be imprecise, especially when considering evacuation disruption scenarios or variable traffic conditions. Other parameters, such as evacuee population, available time windows and shelter capacities, are also often difficult to precisely determine.

Short-notice evacuation thus becomes requiring answering the complex problem which seek to answer *when, where and how to safely transfer late evacuees from assembly points to nearby functioning shelters within a short time window with route disruptions and capacity constraints of shelters and rescue vehicles*. This shapes the problem formulation aim, which frames the research problem context. Figure 1.2 illustrates an evacuation network where each route contains different segments with disruption risk and clearance times.

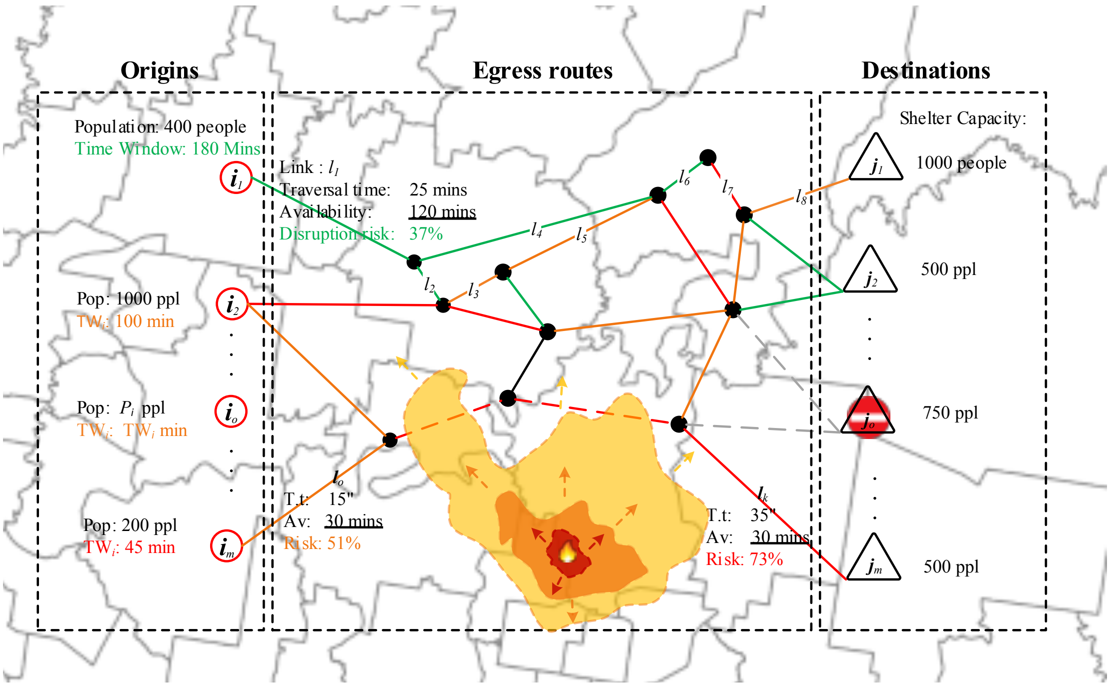



Figure 1.4 Bushfire evacuation network

## 1.5 Research Methodology

This study adopts a quantitative research methodology using advanced optimisation approaches to analyse and model various components of short-notice bushfire evacuation. Optimisation approaches are often applied to choose the best alternatives among all the available decisions. The task of short-notice evacuation is simple yet complicated which needs carefully modelling of multiple factors to safely transfer evacuees from designated assembly points located within the bushfire affected areas to safe shelters (Stepanov, 2009). As shown in Figure 1.3, the operational tasks involve assigning shelter and transferring evacuee through safe routes within a restricted time window.

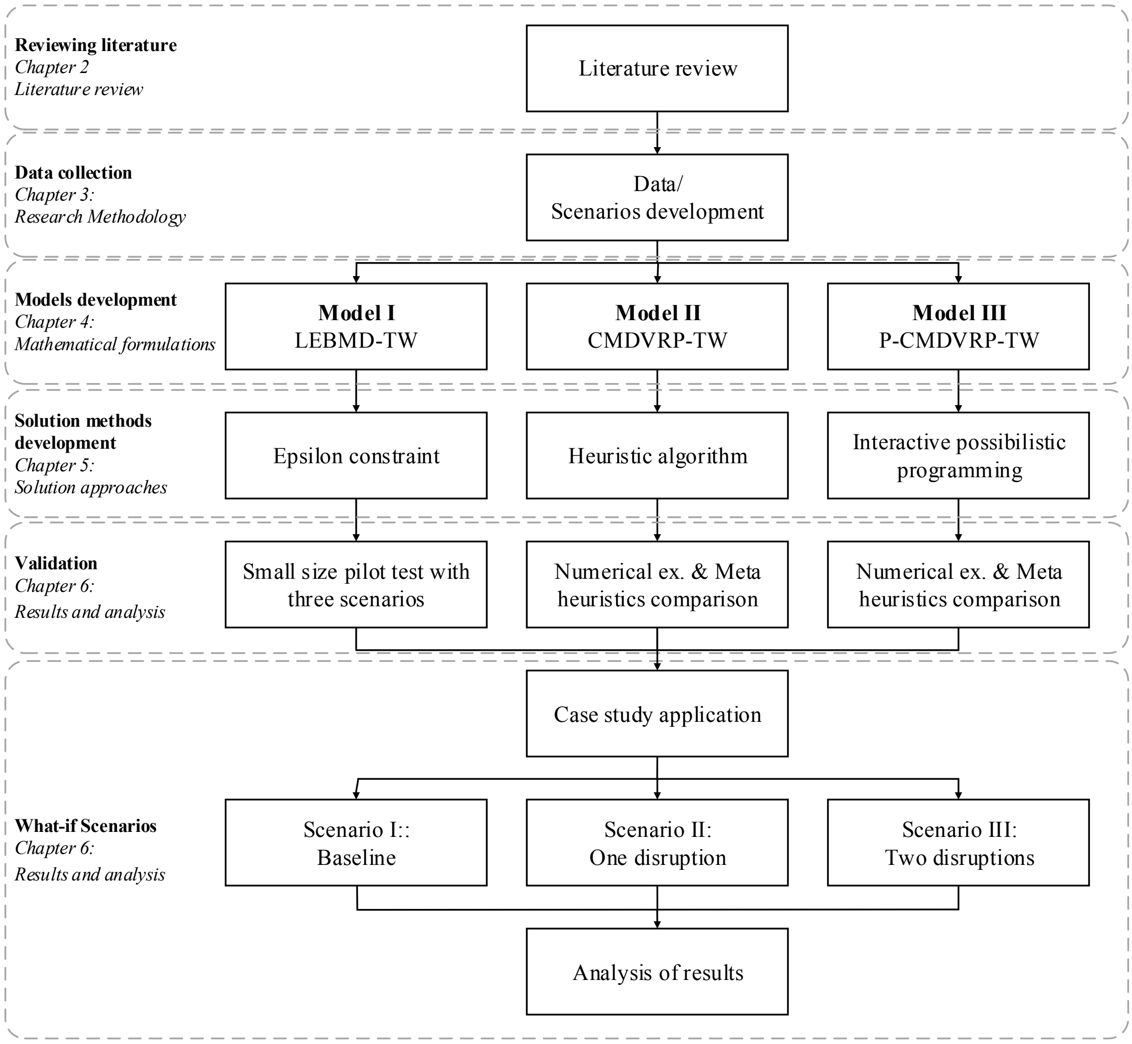



Figure 1.5 Research methodology flow chart

The first stage reviews the extant literature and key theories related to bushfire evacuation modelling which helps to contextualise the research problem, the research questions and the inherent assumptions in developing solutions. Overall, it provides a theoretical\conceptual framework for the development of short notice emergency evacuation models. The second stage relates to the collection, collation and processing of data. It also describes and establishes the situated context of the case study, Murrindindi Shire in Victoria, within which this analysis is carried out. These data sets are then processed to derive inputs and constraints for formulations (e.g., travel times, clearance times, capacities)

The third stage is the modelling stage, which utilises the conceptual framework to contextualise the assumptions used to develop optimisation models to address problems. Three types of modelling approaches are used. Firstly, this research employs a multi-objective programming approach (MOP) to model problem scenarios considering different types of rescue vehicles. Vehicle routing problem (VRP) modelling as a mixed-integer programming approach is also used to model the problem. The uncertainty in the parameters such as evacuees' population, evacuation time windows, and shelters' capacities are also taken into consideration by formulation the third possibilistic model. Overall, the modelling stage focuses on how such Operational Research methods can enhance the emergency response to short-notice bushfire emergency evacuation under different disruption scenarios.

Solution approaches and validation process are provided for each model in generating effective evacuation plans. The model development part of this research examines different optimisation approaches in order to maximise short-notice evacuation, which addresses the main research question. The generated plans will help determining the optimum allocation of candidate shelters, most efficient routes, and number of required vehicles addressing other sub research questions of this study. Finally, the models apply in different bushfire scenarios aiming to "*enhance emergency response to short-notice bushfire emergency evacuation under different disruption scenarios*" to comprehensively incorporate all aspects of short-notice evacuation including evacuation of late evacuees, vehicle assignment, shelter allocation and routing.

### 1.5.1 Study context

The case study context used in this research is the Murrindindi shire, which is located approximately 100 kilometres north-east of Melbourne, the capital city of the State of Victoria in Australia. On 7 February 2009, a day which subsequently became known as Black Saturday, this shire experienced a series of severe bushfires. The first of these commenced to the north of a sawmill in Wilhelmina Falls Road at approximately 3.00pm. The bushfire spread rapidly and by 4:30pm had reached the town of

Narbethong, a distance of more than 50 kilometres. A change in wind direction at approximately 6:30pm caused the fire to sweep through the towns of Marysville, Buxton and Taggerty. Ultimately, the bushfire burnt approximately 168,000 hectares of land and caused massive damage, including the disruption of the source of Melbourne's water supply through key reservoirs. The Black Saturday Murrindindi bushfire caused 40 deaths, 71 casualties, and the dislocation of more than 500 households, mainly in the towns of Narbethong, Marysville and Buxton.

The area for study consists of the six main towns in the area that are at high risk of frequent bushfires with total population of 2160, based on Australian Bureau of Statistics data. One-half (51 per cent) of residents are considered as the emergency late evacuee population based on Black Saturday bushfires research data compiled by the CFA (Teague et al., 2009). Five potential safer locations in adjacent towns were nominated by the CFA (destinations) in order to shelter emergency late evacuees were (CFA, 2014).

In this research, travel times and road capacity data are derived from actual geographical data and travel speed zones maps (VicRoads, 2014). The time windows, bushfire spread intensity, direction and disruptions data have all been derived from the recorded figures for the 2009 Black Saturday Murrindindi bushfire (Victorian Bushfires Royal Commission, 2010). VicRoads bushfire risk assessments have also been adapted as the source for determining the disruption risk for each route.

## 1.6 Thesis structure

This thesis is organised into seven chapters, designed to address the main aim and associated research questions. This chapter introduced the topic, set out the aim and research questions, highlighted the rationale for the research and outlined the research structure; the subsequent chapters are described as follows.

Chapter 2 is an extensive review of the extant literature central to this research topic - bushfire emergency evacuation. It discusses the conceptualisation of the evacuation process in the context of bushfire, behavioural responses to bushfire threat, and linking various components of short-notice evacuation. Overall, this chapter develops a framework for emergency evacuation modelling including a discussion on the meaning and scope of relevant body of literature to help identify the gap in the extant knowledge.

Chapter 3 presents the research methodology, which begins with a description of the study area, bushfire histories, and the 2009 Black Saturday bushfires as a study context. It is followed by a description of bushfire disruptions, which will provide the basis for creating plausible scenarios. Chapter 3 also develops a framework for this research with a particular focus on the generation of bushfire evacuation plans. A description of the research data collection and justification is provided. It then reviews the related methodological formulations for choice of the best optimisation methods. The solution approaches capable of solving the aforementioned formulations are also explained in this chapter.

Chapter 4 focuses on answering the first research question that is *What optimisation approaches can be used to maximise short-notice evacuation under a given set of bushfire scenarios?* It therefore applies three commonly used optimisation approaches to maximise short-notice evacuation. The first model, Late Evacuation during Bushfire under Time Windows to Multiple Destinations (LEBMD-TW), is formulated as a mixed-integer programming approach. The second model, CMDVRP-TW, is formulated using a vehicle routing problem. Finally, the P-CMDVRP-TW integrates the concept of uncertainty in the parameters such as evacuation demand, time windows, travel times, and shelters capacity and vehicle routing problem detailed. Each formulation is accompanied by a list of assumptions in each section, made in order to properly model the problem aiming maximisation of number of evacuated people from affected areas to shelters via safest routes within tight time windows. The notations, parameters and variables and objective functions used for formulation are also provided in each section.

Chapter 5 develops the solution approaches implemented to solve the developed formulations. Pareto-front solutions as non-dominant solution approaches are applied. The epsilon constraint as most common Pareto-front solution algorithms then are adjusted and applied on the first model. In this chapter, a novel heuristic algorithm is developed capable of solving the second and third models. A genetic algorithm is adjusted to evaluate the effectiveness of a proposed heuristic algorithm. For the third model, an interactive fuzzy programming method is applied that is capable of coping with uncertainty in the parameters.

Chapter 6 presents the results of the application of the developed models on the case study area, Murrindindi 2009 Black Saturday bushfires. It includes the results related to the baseline as well as plausible scenarios containing potential major disruptions across the emergency network. This chapter answers the second, third and fourth research questions as *What is the optimum allocation of shelters required to maximise spatial coverage of late evacuees in bushfire affected area?; How can the most efficient routes (i.e. safest and shortest) be determined to transfer people from assembly points to designated shelters?; And how can vehicle assignment and scheduling be optimised to maximise short notice evacuation within a specified time window?* by presenting the results under different bushfire scenarios.

Chapter 7 summarises the key findings of this study and discusses the potential implications of these findings for emergency planning and response. The research questions set out earlier are revisited to evaluate whether they are adequately answered. The chapter discusses the key contributions of this study and the practical implications that arise from the research. Directions for future research, along with key limitations, are also discussed.

## 1.7 Summary

This chapter has established the research context. It has provided the rational for undertaking this research by arguing for the importance of bushfire evacuation and identifying the research problem as an existing gap in the literature. This chapter has presented the research aim and set out four interrelated research questions to be addressed in this study.

This research is important to finding a solution for short-notice evacuations in bushfire contexts which would help mitigate risk in emergency situations. Moreover, this research attempts to address the Victorian Bushfires Royal Commission recommendations for the urgent development of emergency evacuation plans in bushfire areas by developing reliable, integrated optimisation models to improve the efficiency of a short-notice emergency response to bushfires. The proposed novel mathematical modelling approaches seamlessly and simultaneously maximise the number of late evacuees to be safely transported to operational shelters within the available time window through the shortest and safest routes using the most efficient vehicles.

The next chapter introduces the concept of bushfire emergency evacuation and the scope of the extant literature.

# Chapter 2

# Literature Review

## 2.1 Introduction

This chapter defines the concept of bushfire and explains the overall emergency planning and management process. It also provides a background overview of the bushfire evacuation modelling from various theoretical perspectives. The chapter begins by introducing various definitions of disaster, and then contextualises it to bushfire evacuation planning and emergency situations. It then discusses the short notice evacuation component as they relate to shelter allocation and transit-related operations and demonstrates the challenges of bushfire evacuation situations, namely: the impacts of complexity, of multiple conflicting objectives and of how uncertainty can be theorised. The final section of the section provides a summary review of the existing evacuation models and identifies gaps in the existing research literature.

## 2.2 Understanding bushfire disaster

Bushfires are a type of disaster. They are widespread and frequent occur throughout Australia. Bushfires are an integral part of Australia's environment where natural ecosystems have evolved with fires. Bushfires are shaped by physical terrain and coexist with Australia's biodiversity. The majority of Australia's native vegetation is fire prone and extremely combustible and several species, mostly Eucalypts, depend on fire for regeneration (CFA, 2011).

The phrase "disaster", as defined by the World Health Organisation (WHO), is " … an occurrence disrupting the normal conditions of existence and causing a level of suffering that exceeds the capacity of adjustment of the affected community." (WHO/EHA, 2002, p 3). This could by triggered by natural incidents like an earthquake, bushfire or flood or might result from anthropogenic activities, intentional or otherwise (PAHO, 2000). Alexander (1993, p4) defines a natural disaster as "rapid, instantaneous or profound impact of the natural environment upon the socio-economic system". Turner (1976, p 755-6) defines a natural disaster as "an event, concentrated in time and space, which threatens a society or subdivision of a society with major unwanted consequences as a result of the collapse of precautions which had previously been culturally accepted as adequate".

The Country Fire Authority in Australia (CFA) defines a bushfire as "a freely burning, uncontrolled and unplanned fire, which needs to be extinguished. It includes fires in woods or forest; mixtures of scrub, bush and grass; or plantation or nursery stock" (CFA Definitions, 2012). In their definition, bushfires can be classified in four subclasses: spot, small, medium and large. Spot fires are those which affect less than half a hectare. Fires between 0.5 and 5 hectares are called small; 5 to 50 hectares are classified as medium and the rest are classified as a large bushfire. The Black Saturday's fires in Australia burnt more than 50-hectare area, and can be labelled as an extreme fire with more than 450,000 hectares burnt (Victorian Bushfires Royal Commission, 2010).

Bushfires can spread quickly through the landscape, moving at a speed of 4 to 12 seconds per meter and smoulder for a couple of minutes (Victorian Bushfires Royal Commission, 2010, CFS, 2010). They primarily damage farms, crops, livestock and rural infrastructure like fences, power and shedding. Bushfires usually have a low to medium intensity with the ability to propagate fast and instantaneously (CFS, 2010).

In general, bushfires are actually slower moving than grassfires but have high heat radiation. However, in most places in Australia, it is impossible to distinguish between a grassfire and a bushfire because they often occur simultaneously and are colloquially called a bushfire. Bushfires pass an area within two to five minutes, nonetheless they can burn for a couple of days. The spread rate of bushfires and their direction is influenced by various factors, most importantly wind speed and ground slope (Middlemann and Middelmann, 2007). Bushfire can spread at twice the speed for every 10 degree increase in slope. Also, it can be spread twice as fast with just a small change in wind speed (Cheney and Sullivan, 2008, Sullivan, 2009, CFS, 2010).

A bushfire can also be characterised in terms of how it impacts on the affected region. Research shows that the key attributes affecting the evacuation problem in bushfires scenarios include:

- **Intensity:** Intensity refers to the likely loss of property and lives caused by the bushfire. It can be defined by objective measures, normally some disaster specific measures; nevertheless, such measures may not be meaningful to people who are not familiar with them. Instead, the general public is more likely to perceive bushfires qualitatively in terms of the reported severity of damage and/or casualties (Victorian Bushfires Royal Commission, 2010).

- **Spatio-temporal pattern:** A bushfire is time-varying in coverage of its impact. It manifests as a spatiotemporal pattern in terms of how it evolves over time and space (Russell-Smith et al., 2007). This pattern affects the directions in which to evacuate the affected people. It is also important for the determination of stage-based evacuation risk zone (ERZs) (Stepanov, 2009).
- **Effect on the transportation system**: Bushfires can cause negative effects on existing transportation systems, which may be manifested as totally link/node failure or capacity reduction through physical obstruction (such as bridge collapse or inundation), limited visibility (such as smoke) (Johnston and Bowman, 2014) or other risk factors (such as radiant heat or toxic plume) (Teague et al., 2009, Chhetri et al., 2012).
- **Predictability:** The predictability refers to the degree to which the bushfire characteristics can be predicted in advance of an event. The predictability of a bushfire directly affects the ability of the response operators to issue a timely warning and/or evacuation notice, which is correlated to a lead-time to the time point that the fire impacts a spatial location (Stepanov, 2009). This lead-time allows both evacuees and disaster response operators to be better prepared for the emergency evacuation operations (Peeta and Hsu, 2009).

## 2.3 Emergency evacuation

This section reviews literature on evacuation processes and an emergency evacuation planning and discusses the evacuation process phases and the major steps in the evacuation planning procedure. Emergency Management Australia (EMA) (Emergency Management Australia, 2005) has defined evacuation as "a risk management strategy which may be used as a means of mitigating the effects of an emergency or disaster on a community. It involves the movement of people to a safer location. However, to be effective it must be correctly planned and executed" (Emergency Management Australia, 2005, manual 11, p 1). Evacuation is also the "relocation from areas at risk to areas of greater safety" evacuation (Southworth, 1991). Evacuation may differ by objects, scale, and by level of control by emergency services agencies (Sorensen et al., 1992). Evacuation also refers to rescue processes frequently employed in case some communities or infrastructure may be threatened by a disaster (Perry and Lindell, 2003).

An emergency, refers to an event, actual or imminent, which endangers or threatens to endanger life, property or the environment, and which requires a significant and coordinated response (Emergency Management Australia, 2005). Emergency evacuation procedures are known as a frequent approach for managing disaster emergency situations (Furness and Muckett, 2007). Accordingly, emergency evacuation as the most common strategy for handling an emergency situation can be defined as a process which happens when people are confronted with catastrophes, particularly in cases like bushfires, floods, and hurricanes (Perry, 1985).

Emergency evacuation plans are designed to warrant the less risky and most effective evacuation time of all affected people of a town, or area. An emergency evacuation plan determines the key means of responding to event which contains a serious risk of injury or death. An emergency evacuation plan therefore can be stated to be a set of instructions that lays out *who*, *when*, *where*, *and how* to safely exit from the high risk area during an emergency.

### 2.3.1 Emergency evacuation framework

Evacuation is a complex and multiphase process (Stepanov, 2009) (Figure 2.1). In the first phase, an incident is detected. In phase two, risk and potential threats for specific areas have to be estimated by decision makers. Depending on the level of the risk determined and on any lack of adequate shelters, evacuation orders should normally be issued in these areas. These areas include origins of evacuation which in the literature are known as pick-up points (PP), evacuation planning zones (EPZ), or assembly points (AP). In Phase III, a warning alert needs to be issued to inform the affected population. In phase IV, a decision to stay or evacuate should be made by the population. The purpose of this phase in emergency evacuation is to prepare the community/population affected to leave. In the next phase, movement of the population within a transportation network to pre-defined safe areas [destinations] or shelter happens. This phase implies clearing of affected people from hazardous zones. In Phase VI, affected people transfer to safe areas outside of hazardous points. In the final phase verification must be carried out to ensure community/population safely. The average evacuation time, i.e. the intervals for Phases III–VI, may differ from hours to weeks, depending on population size, scale of the hazard, road disruptions, and availability of resources (Church and Sexton, 2002).

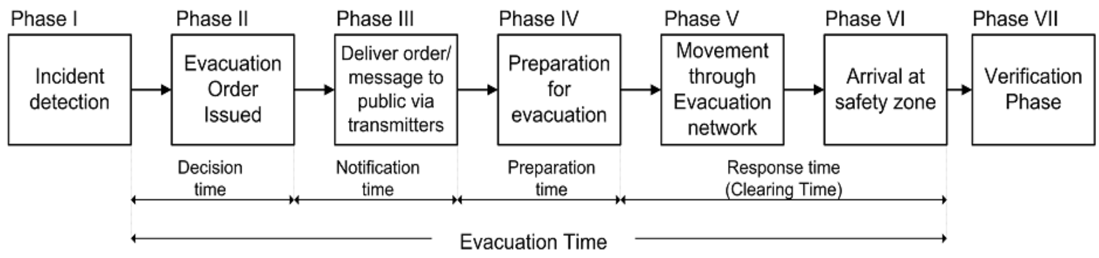



Figure 2.1 Evacuation phases (source: adapted from Lindell (1995))

Based on the scale of a bushfire type disaster which culminates in an emergency situation, proximities, townships, villages or regions may need to be evacuated. The rescue time, as shown above, can vary from hours to days or weeks and depends on the catastrophic extent of the hazard, and may take considerable time, perhaps months (Church and Sexton, 2002). Therefore, quick and nimble responses to evacuate individuals in such emergency situations can save human lives and prevent unforeseen circumstances and crises happening (Shahparvari et al., 2015b). Furthermore, previous studies indicate that the rate of bushfire evacuation is extremely short compared to other types of disasters such as hurricanes and floods. In bushfire disasters, most people do not make a decision to leave their homes until they make sure that they will certainly be affected by the hazard (Southworth, 1991).

### 2.3.2 Short-notice evacuation

On the basis of bushfire predictability, the evacuation problem can be categorised into either short-notice or no-notice evacuations. Short-notice disasters typically provide a lead-time of a couple of hours (Wolshon, 2002). In contrast, a no-notice evacuation takes place immediately after the unexpected occurrence of a disaster, and entails a greater need for pre-disaster planning to enable operations that are more efficient. Examples of such disasters include earthquakes (D'Orazio et al., 2014), terror attacks (Hsu and Peeta, 2013), and spillage of hazardous materials (Burgess, 1999).

Kang et al. (2007) suggest that with a longer lead-time most individuals would go home to get together with household members, and consider securing their property. This course of action is impractical under short-notice evacuation where individuals may intend to get out of the impacted areas as soon as possible. Hence, under short-notice evacuation, people may employ a simple decision process with approximate judgment on a few factors and alternatives, under time pressure due to the emerging threat.

There is an extensive body of literature on emergency evacuation, which incorporates various inter-connected components of an emergency risk management framework such as prevention/mitigation (Chakraborty et al., 2005), preparedness (Perry and Lindell, 2003), response (Shahparvari et al., 2016a) and recovery (Landry et al., 2007). Evacuation, however, is largely related to emergency response, which operationalises safe relocation of evacuees to protected and less vulnerable shelters within a restricted time window (Shahparvari et al., 2015d). The response to short-notice evacuation is dependent on various operations such as an emergency declaration, warning messages, registration and tracing, resource mobilisation and search and rescue (Emergency Management Australia, 2005). Short-notice evacuation is therefore not a discrete operation; it is rather interdependent and interlocked with other operational responses (Shahparvari et al., 2016a).

The interrelated and interlocking sequences and procedures involved in a typical emergency response are shown in Figure 2.2. The system comprises four stages (Shahparvari et al., 2016a): (I) disaster (bushfire) initiation and assessment; (II) input parameters estimation; (III) evacuation plan generation; and (IV) execution of the evacuation plan. In the stage I, the scale, intensity and magnitude of bushfires are assessed. This stage requires the initial inputs (e.g. affected areas, bushfire direction, and transportation network data) to evaluate the potential threat from bushfires. In stage II the operational inputs, which include the number of late evacuees, the number and location of candidate shelters (based on capacity, accessibility and other risk factors), accessibility of routes and most importantly the time windows, are evaluated. In stage III evacuation plans and actions, including assigning rescue vehicles, allocating shelters, and identifying the safest and shortest routes, are evaluated. Generated plans are also re-assessed and moderated in terms of feasibility and soundness in responding to real world situations. Finally, in stage IV, generated evacuation plans are implemented by emergency services agencies including implementing broadcasting evacuation notices or orders, evacuation initiation by transferring evacuees to shelters, assignment of vehicles, and delineation of routes and finally monitoring and control of the evacuation.

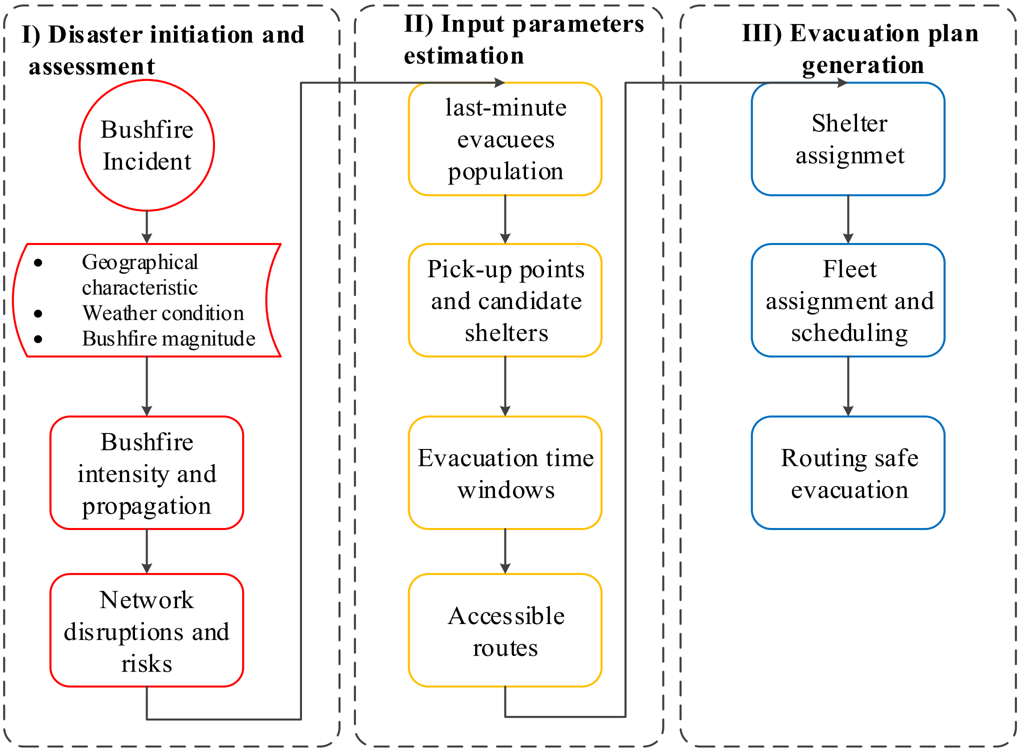



Figure 2.2 Interdependent and interlocking components of the short-notice emergency evacuation process. (source: adapted from Shahparvari et al. (2016a))

### 2.3.3 Bushfire short-notice evacuation practices and procedures

A major challenge in evacuation planning is to determine the distribution order of evacuees to the predefined shelters. To meet this goal, several objective functions have to be considered and met at the same time, even some of the objective functions may conflict with one and another (Chow and Lui, 2002, Georgiadou et al., 2007, Yi and Özdamar, 2007). These functions have emerged from research undertaken on the increasing numbers of bushfires globally.

In the past several decades there has been a sharp increase in fire events in Mediterranean forests (Cameron et al., 2009). In Canada, there has been an rise in both fire occurrence and area burnt (Podur et al., 2002). Increased fire activity has also been seen in U.S. forests with more frequent large fires, longer fire durations and longer fire seasons (Westerling et al., 2006). Extreme fire seasons have also been experienced in recent years in Australia (Teague et al., 2009) and Russia (Kharuk et al., 2007).

In a related research in Finland, a population-location spatio-temporal model has been developed by Ahola (2006) aiming to optimise the risk assessment and failure analysis of emergencies that developed as a result of the bushfire outbreaks. Generally, long-term risk and failure of evaluation planning instead of the short-term emergency response was shown to be preferred in case of an imminent fire. Finnish Fire and Rescue Services utilise a Geographic Information Systems [GIS] model which generates a risk map in accordance with the population, and list of road congestion crashes (Ahola et al., 2007). Their model is designed for urban fires instead of bushfires, and is particularly employed to aid in evacuation planning and resource assignment, nonetheless it is generally possible to modify the model to apply in bushfire in Australia so that when a bushfire starts this will influence the potential implementation of the relevant policy.

Arnol (2007) investigated the various approaches and experiments of disaster management during a bushfire for urban interface fires in. the United States, Portugal, Spain, Italy, Greece and France to find out how Australia could gain knowledge from application of their practices. He noted that the urban interface area is the place where properties and buildings are located on the fringe of bushland so therefore are more likely to face emergencies because of bushfires. Considering the increase in residential population in such regions, and the spread of the urban space, this UI zone is increasing in dimensions\length. Among all the countries studies by Arnol (2007), just France was comparable to Australia, because people are advised to remain and protect their houses and possessions during a bushfire. It is notable that the police are responsible for co-ordinating an evacuation in an emergency in Victoria State, Australia (Guide, 2000). Mandatory evacuation policies are applied in the rest of countries studied by Arnol.

In the United States, local government organisations are in charge in case of any emergency situation, although federal national parks and forest organisations and the state, town, and local police are also responsible (Arnol, 2007). Arnol notes, an 'integrated event command team' is responsible to react and team members all interact with each other to manage the bushfire disaster. In Italy and Portugal, the "Civil Protection Authority" is responsible in case of unforeseen emergency situations either in urban or rural regions. However, there is also another authority called "the National Forestry Department" which is responsible for dealing with fire incidents that occur in forests while they may ask urban fire fighters to help them to rescue evacuees and extinguish the fire. The coordination of responses between emergency services agencies is done from predefined centres known as "operating rooms". In Spain, Arnol notes, the "Civil Protection Authority" has a "Fire Service" subsection with the same responsibilities as other countries, while in France and Greece the "Fire Services" has been structured individually to be in charge of any fire related incidents and of activities such as evacuations or extinguishing the bushfires (Arnol 2007). Almost all of the countries researched had provided urban and pre-urban interface maps to identify and rank which areas were most likely to be faced with bushfire hazards and where forest clearance was required. Then based on the maps, evacuation plans had been designed to define best approaches for the relevant organisation to act with in case of emergency situations.

In Australia, a "Stay or Go" policy transferred the responsibility and decision about staying and protecting the property, or leaving early, to individuals when threatened by bushfires. The Australian 'Stay or Go' policy, which is a replacement of previous plan 'prepare', stay and defend, or leave early', was strategically designed to reduce risk to government agencies by making people responsible for their actions (Paveglio et al., 2008). One key limitation of this policy was the lack of consideration for late evacuees who are not well integrated in the evacuation procedures as stipulated by the "Stay or Go" policy in Victoria (Teague et al., 2009). The policy emphasised the importance of timely evacuation and condemned the policy of prepare and protect. The developed models show the potential risk of staying in bushfire fire affected area or the danger of unorganised late self-evacuation. It therefore provides evidence for public debate on the effectiveness of the "Stay and Go" policy. The failure of this policy is further highlighted and then reformed through amendments to the 'Stay and Go' policy in the form of 67 recommendations to the Victorian Government in July 2010 (Victorian Bushfires Royal Commission, 2010). It resulted in the development of a new national policy, called “Prepare, Act, Survive” (Australasian Fire Authorities Council, 2010).

The “Stay or go” policy is a procedure which is currently in use in all the Australia’s states and territories, however, the application are different. “Stay and go” emphasises that those who have chosen to remain and protect their property must be physically and mentally prepared. So under specific circumstances they may allowed to stay in their properties/shelter until the passing of the bushfire hazard (Victorian Bushfires Royal Commission, 2010). Given the alternative policies, especially the Australian ‘stay or go’ policy as ‘prepare’, stay and defend, or leave early’, was investigated by Paveglio et al. (2008). They also have pointed out that ‘LEAVE EARLY’- might be considered as an option to evacuate, however they argue, not in all interface fire situations.

## *2.4 Short-notice evacuation driving factors*

This section describes the factors affecting short notice evacuation including policy, the behavioural aspects of evacuees, and critical infrastructure and risk. Driving factors in short-notice evacuation can be categorised as follows:

### 2.4.1 Evacuees’ behaviour

In evacuation planning, the decision of individuals/households plays a critical role (Teague et al., 2009). These decisions are an important and valuable aspect of evacuation planning to assess the transportation related problems that may hinder the evacuation (Shahparvari et al., 2015a). The difficulty with these behaviour models in predicting evacuees’ behaviour under uncertainty lies in the complexity of human psychology and cognitive processes (Cova et al., 2011).

The ability to estimate the number of people who would potentially decide to leave early or stay in the area to protect their properties has a strong bearing on evacuation planning and resource allocation (Lindell et al., 2011). There are a wide range of behavioural factors that influence the evacuation decisions, including age, physical capacity, mobility and health of the population; responsibility of children, pets and livestock; and perception of risk and the degree of preparedness. Murray-Tuite and Wolshon (2013) comprehensively reviewed evacuation models in which a broad range of behavioural parameters were incorporated. Their research identified key factors such as the presence of children in the household, older age family members, gender, disability, pets, and fear of looting. These were identified as the key factors driving evacuation decision-making. However, these factors were considered in modelling only in specific types of disaster such as hurricanes (Hsu and Peeta, 2013, Pel et al., 2012) .

Behavioural models for evacuation demand have received a significant amount of attention for many years (Dash and Gladwin, 2007). Behavioural aspects of evacuees during evacuation include how and when they chose to evacuate and the choice of their routes and destinations. The difficulty with these demand models lies in the complexity of human psychology. Other researchers have examined a wide range of factors that affect evacuation behaviour and demand (Baker, 1991, Dow and Cutter, 1998, Dash and Gladwin, 2007).

Current practice in evacuation planning to estimate time-dependent travel demand is a two-step process. In the first step, the total number of people expected to evacuate is estimated using participation rates. These rates are determined by different characteristics of the disaster and the factors affecting evacuee behaviours. In the second step, the time at which evacuees are expected to evacuate is estimated. This is typically carried out using a response (loading) curve which estimates the percentage of total evacuation demand in each time period. A more detailed review on studies related to evacuation demand modelling, are in Yazici and Ozbay (2008) and Pel et al. (2012).

In the case of bushfires, people's reactions can be categorised into three group; those who leave early; those who stay at their properties (Shelter in Refuge) and those who decide to shelter in refuge. Cova et al. (2011) referred to these decision-choices as 'protective actions' (Figure 2.3). Based on these reactions, bushfire evacuations can be mandatory, recommended, or voluntary. In most countries, evacuation during a bushfire is compulsory, however, in Australia and southern parts of France an stay or go choice is given to residents except in the case of a severe bushfire (Arnol, 2007). People are permitted by law to stay and protect their houses and possessions. As shown in Figure 2.3, people have to choice to leave early, or stay in their houses and protect their properties (Shelter-in-place).

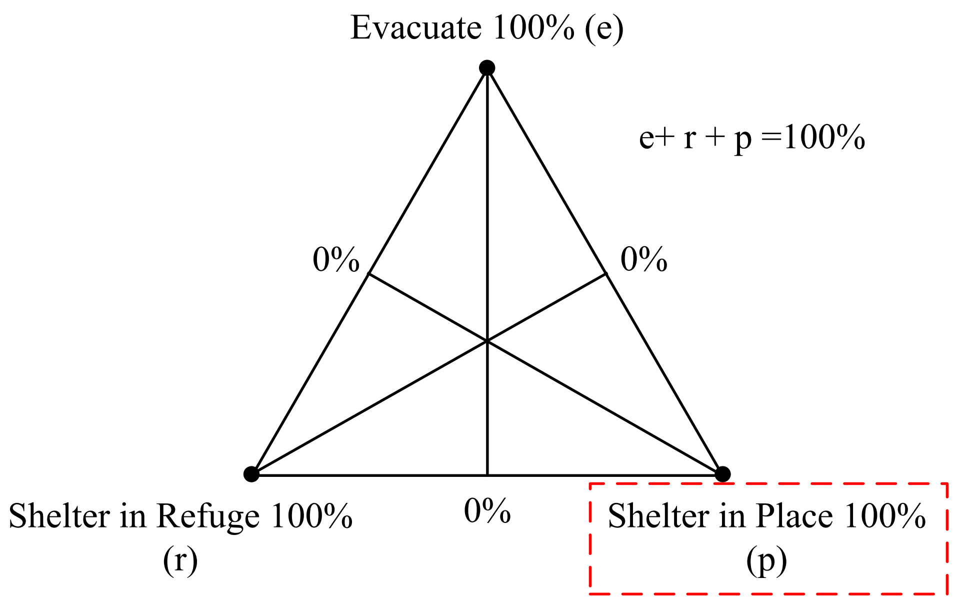



Figure 2.3 Protective actions ternary diagram (source: Cova et al., (2011))

Alternatively, they can take refuge in a shelter. There are, however, people who chose to stay and defend their properties instead of leaving early. People with disability, elders, and parents with children also require additional support. In addition, people with no access to a personal vehicle are also dependent on the emergency services agencies. The decision to stay or leave early is critical as it could cause confronting life-threatening situations.

The decision to evacuate late is considered as a dangerous option (Handmer and Tibbits, 2005, Krusel and Petris, 1992, Whittaker et al., 2013). These studies investigated the risks of late evacuations. The situated knowledge uncertainty of a short-notice evacuation may put evacuees' lives at a greater risk. 32 per cent of all the bushfire fatalities in Australia (176 of 552 deaths) during the last century were associated with short-notice evacuation. Significantly, data shows that over 50 per cent of those who were evacuated on Black Saturday could be classified late evacuees (Haynes et al., 2010).

Another concern with late evacuation decision is evidence showing that many homeowners do not intend to evacuate during bushfire far more than other disasters such as floods (Cohn et al., 2006, Paveglio et al., 2010, Stidham et al., 2011). The tendency for people to wait until a fire arrives before deciding whether to stay and defend or leave is a perennial challenge for fire services (Rhodes, 2005, Teague et al., 2009, Whittaker et al., 2009). Behavioural factors such as stress of being away from their house, uncertainty on when they could return home, and lack of information on status of homes can lead households to stay at their places in case of bushfire (Stidham et al., 2011, Cohn et al., 2006). Others have noted that women and families are more likely to favour evacuation, and able-bodied men tend to stay and defend property. In a field study, Proudley (2008) found that a greater proportion of women (54 per cent) left their homes and properties before or during the fires compared to 35 per cent in men. These findings are consistent with research on gendered responses to bushfire, which has found that women more likely decide to evacuate when confronted by bushfire (Eriksen et al., 2010).

The main concern of late evacuation is that late evacuation increases the chance of confronting fatal dangers that can result in death. The data of respondents to the Bushfire CRC[2]'s household survey 2009, during Black Saturday, showed that (38 per cent) of those who stayed to defend left at some stage while their property was under threat. These late evacuees reported encountering dangers such as smoke (74 per cent), embers (59 per cent), poor visibility (56 per cent), traffic (30 per cent), flames (56 per cent) and fallen trees (37 per cent). The Commission received evidence for road disruptions and reports on people those who injured or died on roads. All 10 people who had no chance to evacuate early perished in the Kinglake area in the Black Saturday fires. Evidence also indicates the lack of knowledge and of unknown situations when evacuating during the Marysville fires along the Buxton-Marysville road, which was cut off from the road network. This shows the severity of leaving late from the bushfire affected areas.

Late evacuation using a personal car is also problematic. Due to flames, smoke, strong winds, fallen trees, traffic and the urgency of the situation, the chance of confronting a bushfire due to driving in an unknown context could increase the chance of injury or fatality if the evacuation is not adequately coordinated (Tibbits and Whittaker, 2007). Communication plays a significant role in such situations, which enables evacuees to be

[2] The Bushfire Cooperative Research Centre (CRC) is "an Australian Government initiative conducting research into the social, environmental and economic impacts of bushfires risk to the community".

informed via radio or phone. The evidence from the 2009 Black Saturday bushfires supports this conclusion (Victorian Bushfires Royal Commission, 2010)

Evacuating people with limited mobility or of special needs is another concern which needs additional planning and preparation. Often, people with disability opt to take shelter in their places until the last minute (Cohn et al., 2006, Paveglio et al., 2010). Perkins et al. (2001) discussed the use of buses to evacuate people (elderly and disabled) under a no-notice scenario. A significant proportion of evacuees including infants or children (23.7 per cent), elderly person\s (4.1 per cent), disabled person\s (2.4 per cent), ill person\s (1.9 per cent), or distressed person\s (5.1 per cent) were shown to need additional support during a bushfire.

Late evacuation is an inherently dangerous response to bushfires (Wilson and Ferguson, 1984, Krusel and Petris, 1992, Handmer and Tibbits, 2005, Haynes et al., 2010) and is not recognised as a best option (Australasian Fire Authorities Council, 2010). It was an effective response for the majority of those who did so in the 2009 Black Saturday bushfires. Most of late evacuees did reach their destination safely, (80 per cent), but they expressed that the danger level was high or extreme while evacuating. 40 per cent perceived that the dangers related to blaze intensity, embers, heavy smoke, disorientation and road disruptions. 14 per cent of late evacuees in that fire died while attempting to evacuate from high risk areas (Handmer et al., 2010). This indicates the potential danger of un-organised self-late evacuation.

### 2.4.2 Evacuation policy

As a result of police reports that 113 out of 173 deaths in the Black Saturday bushfires were found inside their houses, the policy came under scrutiny (113 deaths were inside in houses, 27 deaths outside house, 11 deaths in cars, 5 deaths on roadways, 5 deaths near cars, 6 deaths in garages, 1 death in open land reserves, 1 death in sheds, 4 deaths not within fire location). Further investigation of the deceased victims of the bushfire showed that around 70 per cent had been sheltering passively when they perished (Handmer et al., 2010). It was also reported that another 11 per cent of fatalities had occurred when they had been travelling through bushfire affected areas (Teague et al., 2009).

The Victorian Bushfires Royal Commission was established on 2009 to investigate the reasons for, and impacts of, the Black Saturday fires bushfire. The commission heard evidence about the late evacuation of about 200 people from Marysville as the bushfire engulfed the townships (Figure 3.1).

The key story that emerged was:
*"after outbreak change in wind direction, bushfire had propagated to Marysville at about 6.45 pm. Police started to direct late evacuees with alarm sirens and door-knocks toward Gallipoli Park oval to be evacuated in convoy to Alexandra. Although the evacuation was risky because the Buxton–Marysville Road could have become blocked, each of the three police officers who gave evidence about the evacuation judged that, in this instance, evacuation was safer than remaining on the oval. As it turned out, the convoy reached Alexandra safely. It is not known how many attempted a late evacuation, failed, sought shelter at home and/or subsequently died. The Commission agrees with the fire agencies that late evacuation can be deadly" (Victorian Bushfires Royal Commission, 2010).*

Until Black Saturday most civilian deaths in bushfires in Australia had occurred during late evacuation. The late evacuation fatalities not only occurred during Black Saturday. An inquiry on historical bushfire late evacuation fatalities in Australia during the period (1900-2008) shows that late evacuation has commonly been the action most taken at the time of death, accounting for 32 per cent (176 of the 552 deaths) of all the fatalities (Haynes et al., 2010).

After a comprehensive investigation of series of devastating disasters, issues, response activities, and hearing evidence, the Victorian Bushfires Royal Commission (2010) highlighted the need for amendments in the form of 67 recommendations in its final report to the Victorian Government in July 2010. In particular, the major focus shifted toward the *"necessity of urgent development and improvement of emergency evacuation components such as identification of neighbourhood safer places and potential shelters*", community refuges, allocating resources, bushfire disruption risks. Most importantly, a new policy of the State of Victoria focuses now much more on emergency evacuation which now has been incorporated as a recommended option.

(e.g., see Victorian Bushfires Royal Commission Final Report 2010, Recommendations 1, 3, 5, p 23-24). The Commission also stated that the "Stay or Go" policy did not account for "ferocious" fires, and recommended that Fire Danger Ratings be revised to include a rating beyond 'Extreme', which currently represents "Code Red or catastrophic" indication.  To reflect the serious weather conditions that fed the Black Saturday Bushfires and in situations of catastrophic bushfires, all households should strongly be offered to evacuate regardless of their preparedness and dependability against bushfire. This is evidenced in the Commission statement:

*"This is planned agency-initiated evacuation in the face of an actual threat. It is implemented by police on the recommendation of an Incident Controller. All these actions need to be planned and, ideally, carried out before the arrival of a bushfire. Whether or not emergency evacuation is a viable or likely option should be determined well in advance of a fire. (VBRC final report, 2010, Vol. 2, Chapter 1, Section 1.8.7)"*

These recommendations are now key elements in the national "Prepare. Act. Survive." (P.A.S) Policy (Australasian Fire Authorities Council, 2010). Therefore, designing an effective evacuation plan to transfer people from bushfire-prone areas to shelters within accepted time windows using available facilities and resources has remained a key challenge for bushfire emergency services agencies. The emergency response becomes more difficult as a bushfire spreads and disrupts the emergency supplies and transportation networks (Shahparvari et al., 2015d, Shahparvari et al., 2016b). Under such a situation, the development of an evacuation system requires a modelling approach that is capable of simultaneously considering multiple objectives constraints and scenarios and that is the focus of this research. There is an urgent need for integrating the evacuation process of late evacuees in the current policy "Stay or go". This policy has been recently revised from the earlier version "Prepare, Stay and defend or Leave Early" based on the recommendations from the Victorian Bushfires Royal Commission Report.

### 2.4.3 Bushfire behaviour and propagation patterns

Bushfire propagation patterns in a landscape are an unpredictable due to the effect of multitude of environmental factors. Bushfire Spread Rate (fire front) is mainly influenced by three fundamental elements fuel, topography and weather (Countryman, 2004):

BSR=f (fuel, topography, weather) (2.1)

More importantly, outbreak changes in each element (e.g., wind speed or direction vegetation density, slope) can cause substantial change in bushfire behaviour and pathways (CFS, 2010). Most developed modules also have adapted in a way to be applicable in their respective case study region due to distinct topographical settings. Papadopoulos and Pavlidou (2011) provided a comprehensive comparative review on bushfire simulators. Tools and approaches that aid in an evaluation of likelihood of a fire occurrence, the potential effect on the environment, and spatial and temporal characteristics of fire spread comprise the concept of Fire Behaviour Prediction Systems (FBPS) (Burgan and Rothermel, 1984). The subclass of such systems, Fire Behaviour Calculation Systems (FBCS) (Stepanov, 2009) computes the spatial and temporal extension of the fire perimeters as well as defines bushfire velocity and intensity at any point of the fire line. The primary purpose/function of these systems is to predict the shape, size and expansion of the fire perimeter through complex terrain for given weather conditions (Stepanov and Smith, 2012). This information is absolutely crucial for planning fire extinction and evaluating the hazardous risk for a population (Stepanov, 2009). A rate of fire spread, intensity and length of flame are important measures to evaluate the severity of bushfire.

There are few simulation-based studies aiming to predict the probable areas of bushfire propagation which can be adjusted and utilised as input in a predictive model (Tolhurst et al. (2008), (Stepanov and Smith, 2012). However, the focus of this study is on safe and prompt evacuation rather than mimicking the spatial behaviour of bushfire propagation. The area of study is bushfire prone area that has been affected by a number of minor or major bushfires during last decades. The study of the past bushfires in this region indicates that there is no regular pattern of bushfire spread. The contribution of the proposed research is to develop a general model that is capable to find the optimal pattern of late evacuees' evacuation under any plausible bushfire propagation scenario while the network is disrupted gradually.

### 2.4.4 Critical infrastructures and failure risks

The infrastructure critical in bushfire evacuation consists of pick up points, roads, shelters and rescue vehicles (Shahparvari et al., 2016a). This infrastructure plays an important role in the performance of bushfire emergency evacuation. An efficient transportation infrastructure is fundamental to the development of a responsive and efficient evacuation system (Shahparvari et al., 2016a). Coppola (2006), however, noted a gradual shift toward risk reduction-based disaster management which places greater emphasis on risk mitigation rather than on response.

Network reliability has two dimensions: connectivity of a network and performance reliability (Sanchez-Silva et al., 2005, Bell, 2000). The evaluation of performance reliability for transportation network becomes extremely significant in the post-emergency stage (e.g. earthquake, attack of terrorism and bushfire), because the network reliability directly determines the life security of people who are urged be transported to the safe region. Considering the response of evacuees under emergency, (Wu et al., 2008) developed an evaluation model for a stochastic moving network in which people move in stochastic directions when faced with emergency.

Moreover, emergency sometimes could also result in some unexpected delays and bottlenecks or ITS management failure in the evacuation network (Shabani and Nassiri, 2008). In other words, the infrastructure may not be always accessible. As a route can consist of several segments, bushfires could disrupt routes from different segments. Therefore, each segment of a route has different availability time window within which evacuation has be carried out. Hence, once a fire front hits a road segment, all routes linked to the disrupted segment will no longer be accessible. How to select the evacuation route is critical to improve the efficiency of evacuation, and a better understanding of the reliability of evacuation network can help bushfire emergency services agencies in emergency planning.

Communication is crucial for safe evacuation and accordingly is a key component of effective emergency management operations (Victorian Bushfires Royal Commission, 2010). Tools for communication include mobile and landline telephones, computers, mobile data networks, radio and pager. Evidence demonstrates that the CFA and Victorian Police experienced several communication difficulties or failure on the 2009

Black Saturday (Victorian Bushfires Royal Commission, 2010). These difficulties included:

- Radio black spots, channel congestion and transmission failures
- Fire damaged/destroyed radio and communications infrastructure
- Inadequate pager performance.

Australia's largest telecommunications and media company (Telstra) had to spend $20 million in upgrading and repairing communications infrastructure after the Black Saturday bushfires (Victorian Bushfires Royal Commission, 2010).

Knowledge management systems are another vital component that enables better coordination of bushfire emergency planning and operational responses (Teague et al., 2009). For example, on 7th February 2009, there were various problems with fire management technology at incident control centres. The Department of Sustainability and Environment (DSE) and the Country Fire Authority (CFA) used different knowledge management systems for performing similar tasks. System access was not always available, making it difficult to transfer and use relevant information (e.g. maps, warnings and reports) (Victorian Bushfires Royal Commission, 2010).

## *2.5 Short-notice evacuation planning decisions*

An evacuation plan is to identify safe areas as a critical element of emergency plans. A critical question which needs to be tackled in bushfire evacuation is: where should each evacuee go and from which route? (ElDessouki, 1998). To attain an effective emergency evacuation plan, a decision maker must take into account three important components: the capacities of shelters as safe areas, and the distance to shelters (Negreiros and Palhano, 2006, WU et al., 2006). The following sub-sections provide details on these three components.

### 2.5.1 Shelter allocation

During an emergency evacuation, shelter allocation is an inevitable part of the evacuation process (Lim et al., 2012). Timely allocation of shelters in terms of the optimal number, location and capacity plays a critical role in emergency planning (Alexander, 1993). However, the allocation of a facility as a safe shelter in a bushfire is a risky and time-sensitive decision (Owen and Daskin, 1998). Studies (Chan, 2010, He et al., 2009, Mastrogiannidou et al., 2009) have consolidated location-allocation problems with emergency evacuation routing problems. These studies raised concerns regarding the timely availability of both rescue vehicles and safe shelters, due to uncoordinated pre-emergency planning. Despite the significant contribution of previous studies in transit-based evacuation, due to the computational hurdle posed by the complex facility allocation formulation problem and the potential disruption uncertainties, there has been a limited attempt to integrate transit-based systems with emergency evacuation location-allocation planning.

Coppola (2006) stated that there is also a shift towards risk reduction-based disaster management. Chan (2010) considered the utilisation of uncertainties formulation both prior to, and in the aftermath of, the outbreak of a disaster. However, the uncertainty of the situated context of a bushfire in terms of its propagation rate and direction, as well as the potential for network disruptions and system failure on an in situation response to emergency evacuation has been largely overlooked in most optimisation models. Furthermore, most optimisation models assume that emergency service facilities (e.g. shelters, hospitals) continue to provide services in an emergency situation without any disruptions (An et al., 2013). Yet these facilities are equally as vulnerable to key disaster threats. Their resources are often finite, and are not available when and where they are most needed. In particular, mass transferability in an emergency often exceeds the capacity of evacuation fleets, which subsequently causes significantly longer waiting times and evacuation delays.

Shelters typically are designated to accommodate large numbers of evacuees (Stepanov and Smith, 2009). In most studies, it has been assumed that the majority of public evacuation shelters provide ample space to accommodate evacuees and are located in areas where there are adequate ingress routes to deliver humanitarian, medial and other aids (Campos et al., 2012). While the majority of studies consider shelters in the view of destinations choice (Bish and Sherali, 2013, Campos et al., 2012, Lim et al., 2012, Sayyady and Eksioglu, 2010); others do not take into account shelter in their formulations (Huibregtse et al., 2010, Pel et al., 2012).

There are reliable location models, which have addressed the location-allocation problem of emergency facilities in disaster situations (Shen et al., 2011, Chen et al., 2011b, Berman et al., 2007). However, few models have explicitly considered maximising the transferability of late evacuees whilst simultaneously minimising resource utilisation (Shahparvari et al., 2015d, Shahparvari et al., 2016a)

### 2.5.2 Routing and risk problem

In the literature, there are a limited number of studies focusing on modelling and optimising the use of public transit during evacuation (Lim et al., 2012, Zheng, 2014, Margulis et al., 2006). The studies mainly focused on optimising transit routing plans. A number of studies have developed mathematical formulations to examine the transit-based evacuation routine for both unpredictable (e.g. earthquake) (Sayyady (2007) or predictable disasters (e.g. cyclone) (Chan, 2010, Margulis et al., 2006). For example, in an extended research, Margulis et al. (2006) developed a binary integer-programming model to determine the assignment of buses to pick up points and to shelters during an evacuation. The objective of their model was to maximise the number of evacuee throughput in a given time period. However, their model would assume that buses are at the pickup points at the beginning of the evacuation, and regulate each bus to return to the same evacuation site.

Lim et al. (2012) considered a short-notice regional hurricane evacuation maximising the number of evacuees reaching safety weighted by the severity of the threat. They developed an evacuation-scheduling algorithm to expedite the solution process. Cavusoglu et al. (2012) addressed the importance of transportation needs of transit-dependent and car-less populations and suggested that well-coordinated utilisation of transit assets would lead to safe evacuation of these individuals. In doing so, the study suggested that the behavioural characteristics of evacuees need to be considered along with other factors to make transit evacuation an integral part of evacuation management plans.

Another important consideration is the location of pick-up sites, which can significantly affect the potential for transit-based evacuation services. One way to resolve this issue is outlined by Shahparvari et al. (2015d) in which the problem is solved in order to maximise the number of evacuated people as well as minimise the allocation of resources. Their model is applicable in generating emergency evacuation plans within short time windows. They have applied their model in group bushfire spread scenarios. However, their model has not considered factors such as multiple road connections, inflation time, and the risk of road and segment disruptions. A comprehensive approach is therefore needed to assign shelters using multitude of factors affecting short-notice evacuation.

### 2.5.3 Rescue fleet assignment and scheduling

Short-notice evacuation is often operationalised using a transit-based system. However, the use of personal vehicles is a common means to evacuate which is seen to be problematic due to unknown and uncertain environments such as disorientation, roadblocks, radiant heat (Teague et al., 2009). Also, personal vehicles are difficult to coordinate and would likely exacerbate traffic congestion, which may further hinder the evacuation process. The utilisation of larger commercial vehicles is recommended for a mass evacuation due to their high seating capacity. For example, a bus can carry up to six times as many passengers as a passenger car (Litman, 2006) and therefore has the potential to substantially improve the speed of the evacuation process. However, evacuation using such high capacity vehicles is still broadly missing from the majority of emergency evacuation plans.

Historically, trains and buses have played an important role in evacuation. Zelinsky and Kosiński (1991) examined twenty-seven major evacuations that have occurred in the past fifty years. According to this study, trains and buses were important modes in 20 of the 27 studied evacuations. In ten of these evacuations, the majority of people used trains and buses.

Public transit agencies are capable of providing assistance during crisis situations, performing services such as evacuating victims and transport of emergency personnel etc. In the aftermath of major disasters, public transit has often maintained the mobility of residents faced with damaged or blocked roadway conditions. Successful application of public transit in some of the incidents in recent years highlights the critical role of transit systems including the San Francisco earthquake of 1989 (Public Transit, 1992), the Pennsylvania’s Capitol Area blizzard of 1996 (Harrisburg, 1996, Orlando’s LYNX tornado in February 1998 (Berlin, 1998) and the Manhattan, NY, terrorist attack of September 11, 2001 (Jenkins and Edwards-Winslow, 2003).

Public transit is therefore an extremely versatile and flexible mode of transportation that can play a vital role in supporting evacuations during emergency situations. Transit can play multiple roles in an emergency evacuation, and these roles depend on the nature of the disaster and its location, availability of vehicles and operators at the time of disaster, and the extent of damage, if any, to transit equipment and facilities (Abdelgawad and Abdulhai, 2011).

## 2.6 Bushfire evacuation decision-making theoretical factors

This section theorises the bushfire evacuation decision-making process. It presents a classification of the existing theories and approaches, which explain the short-notice evacuation. Emergency services agencies operate in a difficult decision-making environment. Decision-makers are faced with limited time, constrained resources, extreme uncertainty and multiple objectives that may conflict (Martell et al., 1998). Emergency planners therefore operate in a decision environment that is characterised by high degree of complexity and uncertainty associated with short-notice bushfire evacuation. Further examination of decision-making theories would help the policy makers making the right and prudential decisions in a bushfire context. The review of operational research theories might be helpful in addressing problems and developing solutions. These theories include:

- Complexity theory
- Uncertainty theory
- Multiple objectives or hierarchical conflictive decisions

Operations Research (OR) is the use of an analytical approach to aid make better decision making in complex real-world systems. The central objective of operations research is optimisation (Steuer, 1986), that is “to do things best under the given circumstances”. OR are tools to assist bushfire managers to assess alternatives and make decision to solve certain problem. A variety of approaches are used in OR, such as simulation, mathematical modelling, Markov decision processes, decision analysis, optimisation and queuing theory (Taha, 1982). The majority of these approaches require mathematical models describing the system to be constructed.

OR is a widely used approach in several industries, such as telecommunications, manufacturing, transport, mining, health care, logistics and forestry (Winston and Goldberg, 2004, Wagner, 1969). In North America, OR has been used successfully in assisting bushfire management (Minas et al., 2012). Common OR application include location of facilities, deployment of resources, dispatch of evacuation resources, and routing plans. However, in the context of Australian bushfires, OR tools and approaches are not widely applied.

Multiple-criteria decision-making (MCDM) or multiple-criteria decision analysis (MCDA) is a sub-discipline of operations research decision-making theory. Its key characteristic is that multiple criteria are explicitly considered in structuring and solving decision-making and planning problems. A unique optimal solution for these problems usually doesn't exist and the preferences of decision-makers are used to differentiate between solutions (Tabucanon, 1988, Dyer et al., 1992, Zeleny, 1973, Yu, 2013).

Solving such problems can be interpreted in a variety of ways. It may mean choosing the "best" alternative from a a range of options (i.e. the decision-maker's preferred option). An alternative interpretation of solving may be to select a small set of acceptable options, or grouping options into a variety of preference sets. An interpretation would be finding all non-dominated or efficient options (to be explained later). MCDM problems and approaches are classified differently (Dyer et al., 1992). One major distinction depends on whether the solutions are implicitly or explicitly defined (Tabucanon, 1988). Generally, there are two types of MCDM which are discussed below:

- *Multiple-criteria evaluation problems*: A finite number of solution options are explicitly known at the start of the solution process in these types of problems. Each option is represented by its performance in relation to multiple criteria. Multiple-criteria evaluation problems may be defined as finding the best solution option for a decision-maker (DM), or finding a set of acceptable options. Options may also be classified or sorted. Classifying is a process of assigning solution options to non-ordered sets (e.g. using symptoms to diagnose patients' symptoms) (Triantaphyllou, 2000). Sorting is placing options in a set of preference-ordered classes (e.g. assigning credit ratings to countries).
- *Multiple-criteria design problems (multiple objective mathematical*

*programming problems)*: The solution options are not explicitly known in these types of problems. A mathematical model can be used to find a solution option. The number of solution options is either infinite and unable to be counted (continuous variables) or very large if they are able to be counted (discrete variables) (Zeleny and Cochrane, 1973).

Whether it is a design problem or an evaluation problem, DM preference information is necessary to differentiate between the solution options (Dyer et al., 1992). MCDM problem solution approaches are typically classified according to the timing of DM preference information (Dyer et al., 1992).

Multiple-criteria design problems usually require a series of mathematical programming models to be solved to generate implicitly defined solutions. An approximation or representation of efficient solutions may also be useful. This is known as the posterior articulation of preferences, which implies that the DM isn't involved until after useful solutions are explicitly revealed (Karasakal and Köksalan, 2009). When the mathematical programming models contain integer variables, the design problems become harder to solve. Multi-objective Combinatorial Optimisation (MOCO) constitutes a special category of such problems posing substantial computational difficulty (Gandibleux, 2006).

Optimisation theory is a branch of operations research optimal decision-making theory which encompasses many diverse areas of minimisation, maximisation and optimisation. Optimisation approaches aim to choose the best alternatives among all the available decisions. Optimisation as a concept has many applications. For example, in data analysis, healthcare, the distribution of goods and resources, emergency rescue operations, agricultural planning, biotechnology, telecommunications, engineering systems design, financial planning, inventory control, human resource allocation, manufacturing, military operations, risk management, operations management, and traffic control (see (Ravindran et al., 2006).

- A single numerical quantity (objective function) to be maximised or minimised. For example, the expected return on a share portfolio, organisational profits or production costs, or delivery vehicle arrival time.

- A collection of variables to optimise the objective. The values of these variables can be manipulated. For example, the quantity of shares to be sold or purchased, the resources to be allocated to production activities, or vehicle routes through a road network.
- A set of constraints to restrict the values of the variables. For example, a more resources than are available cannot be allocated to a production process, nor can less than zero resources be assigned.

Optimisation problems may have different mathematical properties within this broad framework. Problems with variables that are discrete or have combinatorial quantities (e.g. vehicle route selection from among a pre-defined possibilities set) need a different approach to problems containing variables with continuous quantities (e.g., resource allocation possibilities).

### 2.6.1 Complexity

Since bushfire emergency services agencies are often faced with complex problems consisting of a large number of inter-related decisions together with resourcing and other operational constraints, complex mathematical model might offer useful solutions. Three key approaches to tackle some of the challenges associated with the complexity of short-notice evacuation are discussed below.

#### 2.6.1.1 Mathematical programming

Mathematical programming (MP) is a field of OR that can assist with such problems (Taha, 1982). MP approaches are concerned with optimisation via the maximisation or minimisation of a quantifiable and explicit objective (Williams, 2009). This is an objective function of the decision variables that is optimised in relation to a series of constraints (Hillier and Lieberman, 2005). There are several categories of MP: linear programming (LP), non-linear programming (NLP), integer programming (IP) and dynamic programming (DP).

Linear programming (LP) optimisation approaches are used when the objective functions and constraints of a problem are able to be formulated as a linear combination of its decision variables (Ragsdale, 2004). Non-linear programming (NLP) models can be utilised for problems with a non-linear objective function or non-linear constraints. Integer programming (IP) approaches feature inputs or outputs that must have discrete whole number values. IP may be useful for modelling problems with "yes or no" decisions, logical connections (e.g. "if" and "then"), or indivisible resources (Wolsey, 1998). IP optimisation models have been applied to a variety of bushfire management scenarios (Minas et al., 2012). For example, the maximal covering location IP model (MCLM) has been extensively utilised in the deployment of emergency services (Church and Velle, 1974). Dynamic programming (DP) is especially useful when a series of interrelated decisions must be made. In deterministic DP for example, the system's state at the next stage is fully dependent on the state of the current system and the associated policy decision (Hillier and Lieberman, 2005).

#### 2.6.1.2 Problem structuring approaches

Problem structuring models (PSMs) are a broad category of approaches. Their purpose is to help structure problems rather than generate a solution (Rosenhead, 1996). They are interactive and participative, normally operating with groups. They are suitable for a range of problem situations where traditional OR approaches (e.g. mathematical programming) have limited applicability. Soft Systems Methodology (Checkland, 1989), Strategic Options Development and Analysis (SODA) (Eden, 1995), and the Strategic Choice Approach (Friend and Hickling, 2005) are the three most widely used PSMs.

Well-structured problems where performance measures, constraints and relations between action and consequence can be clearly formulated are suited to classical OR approaches (Checkland, 1983). However, many bushfire and disaster management problems lack this structure and typically feature intangibles, uncertainties, multiple perspectives and disagreement among experts (Minas, 2013). PSMs can help to overcome some of these issues. PSMs typically utilise rudimentary mathematical or statistical methods by comparison with classical OR approaches (Mingers and Rosenhead, 2004). Expert judgement elicitation and decision conferencing are two relevant PSMs outlined in more detail below.

Expert judgement elicitation (EJE) attempts to minimise bias by obtaining expert opinion in a planned, formal manner. It usually involves surveying or interviewing relevant experts and subsequently analysing their responses, background information and experience. EJE may provide an understanding of amount of disagreement or consensus among experts and the associated reasons. It can be useful in facilitating dialogue and learning (Gregory et al., 2006). In addition, EJE studies are usually a cost-effective and practical approach for obtaining relevant information. EJE approaches have been used in the bushfire context to estimate fire line construction rates and fire containment probabilities. In these situations, alternate approaches to EJE (e.g. observation of experimental or actual fires) are often too dangerous, expensive, and time-consuming (Hirsch et al., 1998).

A decision conference is usually a two-day event where decision-makers from various organisations are brought together to discuss issues and determine a plan or course of action. Discussion in a decision conference is kept focused by a facilitator. A series of decision models are built by an analyst for the purpose of developing a shared problem understanding (French, 1996). Decision conferencing can help with longer-term collaborative decision-making. For example, following the 1986 Chernobyl nuclear accident, a series of decision conferences were held in the USSR. Participants in these conferences included government ministers, policy-makers and scientists. The goal was to identify the major factors influencing relocation and other long-term protective measure decisions. A number of key medical, political and socio-economic factors influencing the protective measures undertaken were successfully identified (French et al., 1992). In much the same way, decision conferencing could be used following major bushfires to facilitate stakeholder discussion and help with disaster recovery planning.

#### 2.6.1.3 System dynamics theory

System dynamics (SD) theory is an approach that helps with understanding complex systems and their non-linear behaviour over time. It uses flows, stocks, time delays and internal feedback loops. In complex systems, components may interact with each another through a web of feedback loops. A small change to input parameters may potentially generate a drastic change to the entire system (Anderson, 1999). System dynamics (SD) can be utilised to model these feedback effects. It can accept the feedback loop structures and non-linearity of real world and physical social systems, unlike many classical 'hard' OR approaches that are both static and linear. While SD uses a 'soft' PSM-like approach to elicit information and structure problems, it does include two 'hard' steps: the model definition level equations and using rate, and the running of model simulations. An SD model demonstrates how the problem is generated in the real world. In addition, it is utilised to test alternative structures and policies (Forrester, 1994). SD approaches have been applied to rural area disaster planning, focusing on hospital surge capacity (Hoard et al., 2005).

### 2.6.2 Uncertainty

Uncertainty can be stated as ambiguities, incompleteness, inconsistency, deception, latency, in the parameters (Camm et al., 2014). Under the uncertainty principle, several parameters cannot be precisely measured or determined. The uncertainty principle derives from the measurement problem or lack of information (Sahinidis, 2004, Diwekar, 2008). Some of the factors causing uncertainties in evacuation problems can be related to population demand and their locations, behavioural uncertainties (e.g., decision to leave or not), disaster characteristics (e.g., direction, rate, and timing of bushfire spread), and disaster impact on the infrastructure ( e.g., road disruptions) (Kulshrestha et al., 2014).

As discussed previously in this chapter, having a suitable and well-established plan beforehand is a requirement for a practical and successful evacuation. Such an evacuation plan should consider the complexities and uncertainties involved in real world transportation network. The exact number of evacuees is highly uncertain. For instance, as shown by Lindell and Prater (2007), there was a big difference between estimated number of evacuees 686.000 and the actual number of evacuees 1,800,000 from the Great Houston area during hurricane Rita, USA. There may be other sources of uncertainties like bushfire propagation rate, time windows and capacity. The following theories can be utilised to deal with this uncertainty.

#### 2.6.2.1 Simulation theory

Real-life stochastic systems that evolve in a probabilistic manner over time can be modelled using simulation theory. The real-life system's performance is replicated in simulation theory via probability distributions used to generate system events (Hillier and Lieberman, 2005). In terms of considering uncertainty in decision support systems, simulations are an easily applied, robust approach (Mowrer, 2000). However, even for small problems, simulation optimisation is often slow. (Minas et al., 2012). Simulation models require validation prior to their implementation to ensure they accurately represent the system under analysis and that they generate reliable results (Winston and Goldberg, 2004).

Several decision support systems used in strategic planning by bushfire emergency services agencies feature simulation models. For example, the California Fire Economics Simulator version 2 (CFES2) simulates daily fire occurrence. It is a stochastic simulation model. Simulation using many years of data enables “what if” analysis when organisational components (such as staff schedules, dispatch rules and resource stationing) are changed (Fried et al., 2006). However, while manipulating simulation models may provide valuable problem insights, the major shortcoming of the simulation approach is that only “the best” option from those investigated is able to be found. It is unlikely that simulations will generate a near-optimal solution for large problems with many options. Mathematical programming (MP) approaches that systemically explore the solution-space may therefore be more likely to add significant value to complex bushfire management problems (Hof and Haight, 2007).

#### 2.6.2.2 Probability theory

Probability theory is used for the mathematical analysis of random phenomena. A random event’s outcome cannot be ascertained before it occurs, however several possible outcomes may be determined. Chance determines the actual outcome. (Feller, 1968, Kolmogorov, 1950, De Finetti et al., 1974). Stochastic (or probabilistic) programming (SP) combines mathematical programming approaches and probability approaches for optimisation problems with uncertain data. It can be used when uncertain model parameters contain known or estimated probability distributions (Kall and Wallace, 1994). Parameter distributions can be either discrete or continuous. In some cases, they can be generated via simulation approaches. Optimisation of the expected value of the system (or the mean outcome) is the most common SP objective. An alternative formula is the optimisation of a weighted sum of variance and expected value. This incorporates the risk preferences of decision-makers (Snyder, 2006). Compared to those generated by deterministic MP models, the solutions of SP models are less sensitive to data uncertainty. Large SP models may however be difficult to solve

(Minas et al., 2012).

The two-stage model with recourse is a common SP formulation. A first-stage decision is made, followed by the occurrence of a random event. In the second stage, a recourse decision is made to compensate for any undesirable effects of the first decision and the random event (Yao et al., 2009, Kall, 1979). Such two-stage SP models have been applied to a variety of disaster management problem scenarios, such as first-aid commodity transportation on a disaster-affected road network (Barbarosoğlu and Arda, 2004) locating storage facilities and developing transportation plans for flood-relief operations (Chang et al., 2007), and determining suitable locations for emergency supplies in a hurricane-threatened region (Rawls and Turnquist, 2010) ((Fried et al., 2006). Probabilistic SP approaches (e.g. chance-constrained programming) require a constraint holding's probability to be higher than a defined threshold (Snyder, 2006). A related approach is stochastic dynamic programming (SDP). This is utilised for problems containing uncertain sequential decisions. Unlike deterministic DP, probability distributions govern state-to-state system transitions in SDP (Bertsekas et al., 1995).

#### 2.6.2.3 Robust optimisation theory

Robust optimisation (RO) theory deals with optimisation problems where a measure of robustness against uncertainty is sought. This may be represented as deterministic variability in the parameter values in the actual problem itself, and/or in its solution. RO is like SP in that it is a constructive approach for solving optimisation problems with uncertain data (Vladimirou and Zenios, 1997). However, unlike SP, the probability distributions of uncertain parameters are not necessary in RO. The uncertain parameters only need to belong to an uncertainty set that may be either continuous interval or discrete (Ben-Tal and Nemirovski, 2002).

RO models are far more difficult to solve than deterministic MP approaches. However, they are also comparatively far less sensitive to data deviations. There are a variety of ways to formulate RO models. The minimax formulation is a highly conservative approach that aims to minimise the maximum damage (cost) across all possible scenarios. It generates costly solutions for worst-case scenarios (Snyder, 2006). Further, a solution generated by an RO model is unlikely to remain both optimal and feasible across all scenarios unless the model has significant redundancies built into it (Vladimirou and Zenios, 1997).

Robust model and solution approaches aim to balance feasibility and optimality depending on the degree of risk aversion of the decision-maker. Restricted scenario approaches minimise the maximum damage (cost) across a restricted reliability set of scenarios. The decision-maker specifies this reliability set of scenarios based on their risk preferences (Snyder, 2006). RO approaches have been applied to facility location under uncertainty (Snyder, 2006) and evacuation transportation planning (Yao et al., 2009).

#### 2.6.2.4 Fuzzy set theory

Fuzzy sets are sets where components have degrees of membership. Fuzzy sets were introduced by Zadeh (1975) and are useful when uncertainty is about imprecision and ambiguity. Fuzzy set theory can be applied to problems containing fuzzy quantifiers (e.g. 'often' or 'least'), fuzzy probabilities (e.g. 'unlikely' or 'likely'), and fuzzy predicates (e.g. 'safe' or 'large'), (Smithson, 1991). In contrast, stochastic programming and robust optimisation approaches are appropriate for problems where uncertainty is mostly due to randomness (Verderame et al., 2010). Set membership is evaluated in binary terms in classical set theory (i.e. an element belongs to a set or it doesn't). Degrees of membership ranging from 0 to 1 are permitted based on a fuzzy membership function in fuzzy set theory (Dubois and Prade, 1988).

The major challenge for emergency services agencies is that multiple factors such as demand, supply, and disaster characteristics which are uncertain in nature, need to be considered in emergency evacuation planning. In some scenarios, it may be difficult to frame the problem parameters as exact values, due to insufficient historical data available to analyse. In other situations, data and probability distributions may be very time-consuming and difficult to source (e.g., patterns of wildfire propagation) (Kulshrestha et al., 2014). In addition, time window calculations for each town tend to be difficult to model deterministically (Zhao et al., 2010b). Instead, they should be represented by interval ranges (Dubois and Prade, 1991). In addition, travel time may often be imprecise, especially when considering evacuation traffic scenarios (e.g., based on past experience, it may be "optimistically 35 minutes and pessimistically 55 minutes", "between 35 and 55 minutes", or "around 1 hour". Other parameters, such as evacuee population, available time windows and shelter capacities, are also often difficult to precisely determine. Triangular fuzzy numbers are used to satisfy the above uncertainties in emergency evacuation planning, as assigning a set of crisp values to ambiguous parameters is not appropriate. It is argued that using such sophisticated approaches in real-time evacuation planning decisions would save both time and money, achieving two major objectives of evacuation management systems (Graat et al., 1999).

### 2.6.3 Conflicting objectives

#### 2.6.3.1 Multi-objective optimisation

Multi-objective optimisation (also known as multi-objective programming, vector optimisation, multi-criteria optimisation, multi-attribute optimisation or Pareto optimisation) is an area of multiple criteria decision-making that is concerned with mathematical optimisation problems involving more than one objective function to be optimised simultaneously (Deb, 2014, Karim, 1999, Taha, 1982, Cochrane and Zeleny, 1973). Emergency evacuation requires optimising multiple objectives in the course of transferring late evacuees to safe shelters (Shahparvari et al., 2016a). An optimisation problem minimises or maximises a certain objective function, subject to supply, demand and time constraints. However, to find a set of Pareto optimal solutions, multi-objective models have more than one objective function (Taha, 1982). A Pareto optimal solution requires that none of the objectives is capable of being improved without making another objective worse. Trade-offs among the various objective values can be examined by decision-makers in order to evaluate the alternatives from the set of Pareto optimal solutions. A level of decision transparency is provided by this structured exploration and explicit identification of trade-offs (Gregory et al., 2006).

Multi-objective models, however, are formulated with more than one objective function to find a set of Pareto optimal. A solution is Pareto optimal if none of the objectives can be improved without making another objective worse. Decision-makers can assess alternatives from this set of Pareto optimal solutions by examining trade-offs amongst the various objective values. This explicit identification and structured exploration of trade-offs provides a level of transparency in the decision process (Gregory, et al., 2006).

Cohon (2004) identified a number of objectives, such as clearance time, number of evacuees, and allocation of finite resources to be critical in emergency evacuation decision-making. Time is considered as the most common objective function in an emergency evacuation. A number of studies have minimised evacuation travel time (Liu et al., 2007, Tuydes and Ziliaskopoulos, 2004), network clearance time (Sattayhatewa and Ran, 2000), and mobilisation time (Sbayti and Mahmassani, 2006). Multiple objective functions have been formulated with the aim of improving the efficiency of the evacuation process, by minimising travel or clearance time (Abdelgawad and Abdulhai, 2010, Sayyady, 2007)

Sayyady (2007) formulated the car-less evacuation problem, utilising a minimum cost flow model with additional constraints. Bus stops are assumed to be the pickup locations in this model. During an emergency, the car-less (individuals or groups) are directed to the nearest bus stop to wait for pickup. Evacuation routes for buses are identified by using a “Tabu search approach”. Buses only perform a single trip and do not return after leaving their affected area to pick up any remaining car-less people.

Mixed-integer linear programming models to find optimal transit evacuation routes have also been developed in other studies (Tunc et al., 2011, Sayyady and Eksioglu, 2010). Abdelgawad and Abdulhai (2011) presented a mass transit system that can be harnessed to evacuate transit-dependent travellers in no-notice evacuation events. However, real-time location-allocation and routing of late evacuees to shelters are subject to a range of other factors which should also be simultaneously optimised while operating within a range of stringent constraints (Negreiros and Palhano, 2006, Li et al., 2012). These factors include real or perceived risks, capacity constraints, travel time and network distances, and susceptibility or vulnerability to disaster. The ultimate objective is to safely transfer late evacuees to shelters within the shortest period of time with limited resources.

#### 2.6.3.2 Vehicle Routing Problem

The Vehicle Routing Problem is a well-known integer-programming optimisation approach. Dantzig and Ramser (1959) first proposed VRP. Clarke and Wright (1964) subsequently developed the approach, and it has since been well-studied in a variety of different applications (Liu and Lai, 2011, Solomon, 1987, Gutiérrez-Jarpa et al., 2009, Bertsimas, 1992). There are several survey papers on the VRP, VRP variants, and their solution algorithms and approaches. A classification of the problem was given in Desrochers et al. (1990). Laporte and Nobert (1987) presented a survey of exact approaches to solve VRP. Other surveys that provided exact and heuristic approaches were presented by Christofides et al. (1981), Magnanti (1981), Raff (1983), Laporte (1992), Fisher (1994), Toth and Vigo (2014). An annotated bibliography was proposed by Laporte et al. (2000).

VRP falls into the category of NP-Hard complex problems (Laporte et al., 2000). Being NP-Hard means that the computational effort required for solving this problem increases exponentially with the problem size (Laporte, 1992, Golden et al., 2008). The vehicle routing problem approach has been widely utilised within evacuation optimisation problems in order to balance these competing objectives. The vehicle routing problem (VRP) is an integer programming and combinatorial optimisation problem that aims to use a fleet of vehicles to efficiently service a number of customers (e.g., evacuees in an emergency evacuation situation who need to be safely transported to shelters).

The majority of existing research has examined VRP variations, by adding some constraints to the base case VRP formulation and investigating heuristic solution algorithms and introducing exact solution approaches. Eksioglu et al. (2009) provided a useful taxonomy:

- Capacitated VRP (CVRP): Vehicles have a pre-defined limited capacity.
- Distance-Constrained VRP (DCVRP): The maximum tour length is limited.
- Multiple Depot/Destination VRP (MDVRP): The vendor uses many depots to supply the customers.
- VRP with Pick-Up and Delivering (VRPPD): Vehicles may return some goods to the depot or other pick up points.
- Split Delivery VRP (SDVRP): Evacuees may be served by different vehicles.

- VRP with time windows (VRPTW): VRP-TW is the traditional VRP problem with the addition of evacuee time window limitations.
- Stochastic VRP (SVRP): Some values, such as number of evacuees, travel time are stochastic variables.
- Dynamic VRP: DVRP some elements, such as the availability of a link, may be variable over time.
- Multi-Destination VRP (MDVRP): In contrast with classic VRP, includes visiting a destination more than once.

## 2.7 Modelling approaches

In this study, a multi-method approach to short-notice bushfire evacuation is adopted so as to formulate the bushfire evacuation problem and to compare the outputs of different methods. These are discussed as follows.

### 2.7.1 Mixed-integer multi-objective optimisation

Mixed-integer multi-opjective optimisation is known as a mathematical optimisation formulation with multiple objectives that some of the decision variables are intetegres. Real-time assignment of evacuees to a shelter is affected by a range of factors, including its capacity, distance, and susceptibility or vulnerability to the hazard (Li et al., 2012, Negreiros and Palhano, 2006). Other objectives should also be simultaneously optimised while operating within a range of constraints. Allocation of shelters, in terms of optimal location, number and capacity, is critical to emergency planning (Alexander, 2000). Concerns over unplanned evacuation resources such as lack of rescue vehicles, indicates that shelters availability may be a reflection of uncoordinated pre-emergency planning. Furthermore, sufficient attention has not been given to the integration of transit-based systems with the emergency evacuation location-allocation in the frame of OR/MS (Operations Research/Management Science). The focus of this research is therefore on analysing the operational aspects of the late evacuation process, that is, the transfer of people from assembly points to the designated shelters. There are only a few studies that have employed multi-objective optimisation models for late evacuation problems (Shahparvari et al., 2015c, Stepanov and Smith, 2009, Shahparvari et al., 2016a). The majority of studies have focused on minimising the total evacuation time without considering other objectives such as resource utilisation or area coverage (Abdelgawad and Abdulhai, 2010).

Therefore, the first model developed and applied in this research aims to apply an optimisation approach to deal with the multi-objective evacuation problem to generate possible solutions to improve bushfire evacuation planning. A typical evacuation problem contains various objective functions, uncertainties and constraints, which makes the multi-objective programming much more appropriate. Multi-objective optimisation (MO) is an approach that is suited to these types of problems. Hence, a multi-objective (MP) method is firstly utilised to formulate the problem.

### 2.7.2 Uncertainty and the vehicle routing problem (VRP)

Due to the associated uncertainties during an evacuation, it is unlikely that the evacuation process would go according to the predetermined plan. There are significant consequences of uncertainties during real-life mass evacuations and the entire evacuation planning may fail. Past experience has shown that uncertainty might lead to overcrowded shelters, high network congestion and other failure situations due to underestimation. For instance, it was found that the actual number of evacuees during Hurricane Rita from the Galveston and Harris Counties equalled 1.8 million people, whereas the predicted number was only 686,000 (Lindell and Prater, 2007).

Although the real-life evacuation process is affected by uncertainty, the general state-of-the-practice ignores the real world uncertainties and assumes fixed demand and capacity. In order to avoid the undesirable surprises during the actual evacuation process, it is essential to develop evacuation plans which could guarantee a high probability of the actual evacuation to be as close as possible to the predicted one (i.e. high confidence level). Therefore, while planning for optimal evacuation measures, it is important to deal with these uncertainties and decisions must be made by accounting for different measures of uncertainties (Kulshrestha et al., 2014, Yao et al., 2009).

In the literature, there are few studies in evacuation planning focusing on uncertainty. The majority of existing evacuation planning models assume deterministic approaches (Lim et al., 2015, Kulshrestha et al., 2014). Clearly, there is an inconsistency between this deterministic assumption and what is actually experienced in practice. Taking a deterministic approach might lead to sub-optimal evacuation strategies with potentially significant consequences in the real world.

On the other hand, despite a great deal of research dedicated towards evacuation planning, there is a lack of modelling efforts in the literature addressing uncertainty during evacuation. A few studies have considered uncertainties in evacuation modelling. Yazici and Ozbay (2007) incorporated uncertainty in their Cell Transmission Model (CTM) based System Optimal Dynamic Traffic Assignment (SODTA) model. They approached the problem from a stochastic programming perspective and used a chance constraint approach to model the uncertainties in road capacity during evacuation. Changes in clearance time and spatial shelter utilisation were analysed and it was demonstrated that introducing probabilistic link capacities can adjust the overall flow in the network as well as shelter utilisation. However, it was assumed that the total number of evacuees is deterministically known.

Later, Yazici and Ozbay (2010) also included the demand uncertainty in their modelling approach and proposed a system optimal dynamic traffic assignment (SODTA) model with probabilistic demand and capacity constraints during evacuation. The problem was modelled based on two different stochastic modelling approaches, namely individual chance constraints and joint chance constraints. It was shown that the model can incorporate different user defined probability values and can be used to calculate the change in clearance time, average travel time and risk exposure measures.

While the work by Yazici and Ozbay (2010) is certainly an improvement over previous studies assuming deterministic parameters, they adopt the implicit assumption of chance constraint programming that the probability distributions of random demand and capacities are explicitly known. However, this might not be the case because of the very limited or non-existent historical data on evacuations.

Yao et al. (2009) considered evacuation in an uncertain environment and proposed a robust linear programming model considering demand uncertainty. In their study, the demand for evacuation was explicitly considered to be a random variable. They realised the fact that it is not possible to obtain the exact probability distribution of number of evacuees. Road capacities were assumed to be deterministic. It was found that a robust solution improves both feasibility and quality compared to a deterministic solution.

Ng and Waller (2010) presented a CTM-based evacuation route-planning model that accounts for both evacuation demand uncertainty as well as road capacity uncertainty. Their model also does not require the assumption that probability distributions are known explicitly. A novel distribution-free approach is used to provide probabilistic guarantees on the resulting evacuation plan, i.e. they allow for infeasibilities with a pre-specified tolerance level. It was demonstrated that the reliable evacuation plans were able to provide a good estimate of realised evacuation time.

Huibregtse et al. (2010) presented an approach to optimise evacuation measures under uncertainty. The uncertainty in the evacuation problem is related to evacuees (the demand and the behaviour of people) and the hazard (location, time, and intensity). They adopted a scenario-based uncertainty approach (the uncertainty is translated into scenarios which could occur) and defined different criteria to evaluate the effectiveness of evacuation measures. Although the scenario-based approach has some restrictions for real applications, this case study showed the usefulness of dealing with uncertainty in the evacuation problem.

Pel et al. (2010) performed a sensitivity analysis to identify and quantify the impacts of variations in both travel demand and network supply for evacuations. Sensitivity analysis was done using a macroscopic evacuation traffic simulation model EVAQ. The authors varied different aspects such as trip generation, departure rates, route flow rates, road capacities and maximum speeds. It was found that the departure rates and route flow rates have a substantial non-linear impact on the network conditions and arrival pattern, in particular when the network is highly congested, while the trip generation and road capacities have a smaller quasi-linear impact.

For finding a solution that is robust to the changes in number of evacuees, the problem with uncertain number of evacuees is modelled in this research. The model incorporates uncertainties (e.g. real-time constraints in bushfire propagation at escalating rates; gradual disruptions in road and shelter accessibilities; adverse time windows). The uncertainty in the number of evacuees and time windows are considered utilising the fuzzy set theory in this study, which is further explained in more details in Chapter four.

## 2.8 Public transit emergency evacuation

The development of VRP to include high levels of uncertainty in input parameters should be extended to provide a robust solution to complex multi-criteria emergency evacuation problems. As shown in Table 2.1, there are only a few studies that have applied VRP on specific disasters whereby various OR approaches are implemented to solve evacuation-routing problems. The VRP were applied on predictable (e.g., hurricane, bushfire; see (Margulis et al., 2006, Shahparvari et al., 2015a) and unpredictable disasters (e.g., earthquake, terrorist attack; see (Sayyady, 2007, Pourrahmani et al., 2015). Furthermore, most studies have assumed a single time window constraint for the entire network, which may not necessarily mimic the real case phenomenon. There are, however, a few studies that have considered different time windows for each of the road segments to model the network risk in a bushfire situation in Australia (Shahparvari et al., 2015a, Shahparvari et al., 2016a). Uncertainty in input parameters representing the situated context of a disaster, however, is often overlooked in evacuation studies (Kulshrestha et al., 2014, He et al., 2009). The incorporation of uncertainty associated with bushfire propagation, available time-windows within which evacuees need to be transported to safe shelters and travel times should be considered as a vital constraint in emergency evacuation modelling. The deterministic approach to public transit evacuation modelling is relatively less effective in solving the complex problem such as the case with bushfire emergency evacuation.

Ascertaining the right objectives in the correct measurement is critical to the reliability of optimisation solutions. Evacuation problems are generally solved in the form of mixed-integer linear programming optimisation problems that maximise/minimise a specific objective function, subjected to demand and supply and time constraint. The goal of improving the efficiency of evacuation has been formulated into numerous objective functions. Cohon (2004), for example, suggested objectives such as the availability of resources and the clearance time to improve the effectiveness of evacuation decision-making. Time is the most common objective function in the existing emergency evacuation research literature. The time factor includes minimising mobilisation time (Abdelgawad and Abdulhai, 2010, Sbayti and Mahmassani, 2006), minimising network clearance time (Sattayhatewa and Ran, 2000, Sbayti and Mahmassani, 2006) and minimising evacuation travel time (Liu et al., 2007, Tuydes and Ziliaskopoulos, 2004). However, the allocation and routing of late evacuees to safe shelters is also subject to a range of other objectives, such as the levels of risk and unmet demand. The difficulty is to simultaneously optimise these objectives within a range of stringent constraints to generate the optimal solution (Li et al., 2012, Negreiros and Palhano, 2006) to enable safe transportation of late evacuees to secured shelters within the clearance time. The vehicle routing problem approach has been widely utilised within evacuation optimisation problems in order to strike a balance among these competing objectives.

There is little research that has considered reliability of routes in the public transit evacuation planning. Several studies have assumed that fleet, once assigned, only carry out one single trip (Perkins et al., 2001, Pourrahmani et al., 2015) or return in a fetch service (Shahparvari et al., 2015c, Zhang and Chang, 2014), considered routing of fleet although they assumed that there is only one-time window constraint for the entire network. More recently a study by Shahparvari et al. (2015a) has integrated routing and scheduling of rescue vehicles within the entire network by considering different time windows for different segments of road network in bushfire affected area. However, their model has not addressed the reliability of routes and uncertainty in the input parameters.

## 2.9 Summary

Short-notice emergency bushfire evacuation was discussed and presented as operational problems. This chapter discussed the ways this problem was addressed in the extant research literature. The chapter has also highlighted possible theoretical underpinnings for the research and, most importantly, the need for investigation of the driving factors of bushfire evacuation decision-making such as the role of uncertainty and operational complexity.

Two critical decision making components for transit evacuation planning were discussed: public shelter locations and pick-up locations (assembly areas). It has already been shown in the existing research literature that shelter location decisions are extremely important for evacuation planning and can greatly influence the evacuation process. Likewise, public sheltering was shown to be an important component of transit evacuation planning and the location of public shelters can be critical to the efficiency of transit evacuation.

This chapter has also reviewed a range of OR theories and related approaches and discussed their ability to address some of the major challenges of bushfire evacuation focusing on complexity, multiple conflicting objectives and uncertainty concluding that:

- Effective development of an emergency evacuation plan is challenged by complexity, uncertainty, and multiple hierarchal conflictive or non-conflictive objectives, criteria and constraints;
- There exists a concerning and sizeable gap between the decision support needs of emergency services agencies and the decision support tools currently available;
- Operations research (OR) can provide a suite of tools to assist emergency planners and policy-makers to assess alternatives and make decision in this challenging environment. However, many OR theories are complementary and can be used in conjunction with one another.
- Problem structuring approaches (PSM) can be used to elicit objectives and opinions and to help develop a common understanding. The dynamics of complex systems can be modelled using both simulation and system dynamics (SD) approaches. These enable insights to be gained into problem structures and potential management decisions via “what-if” analysis.
- Optimisation related approaches such as mathematical programming (MP) and VRP has become most widely used methods to explore decision-making and seek appropriate solutions from the many alternatives; and
- The majority of extant research studies have focused on minimising the total evacuation time, without considering other objectives such as resource utilisation or area coverage. There has been no comprehensive attempt to model short-notice bushfire evacuation in the policy context that addresses key operational challenges and combines the problems of timely evacuation, shelter

assignment and routing under disruption risks.

This research then attempts to bridge these gaps by developing a reliable optimisation multi-objective mathematical model in order to generate possible solutions to enhance emergency evacuation response in bushfire planning. The next chapter introduces the related research methodology and discusses the approaches adopted to formulate the emergency evacuation problem.

Table 2.1 Classification of public transit (bus) emergency evacuation optimisation literature
(MILP-Mixed-integer linear programming, NLP- Non-linear programming, ILP, PMILP- Possibilistic MILP, Integer linear programming, Dt-Deterministic, St-Stochastic,)

| **Author** | **Modelling method** | **Data** | | **Objective\s** | **Solution approach** | **Disaster type** | **Case study** |
|---|---|---|---|---|---|---|---|
| | | **Dt** | **St** | | | | |
| Perkins et al. (2001) | Static | × | | Minimise network evacuation time | Simulation | Gas leakage | North Carolina, USA |
| Margulis et al. (2006) | MILP | × | | Maximise number of transferred evacuees | Exact solution | Hurricane | Miami, FL, USA |
| Sbayti and Mahmassani (2006) | MILP | × | | Minimise network evacuation time | Iterative heuristic | General | Numerical example |
| Pages et al. (2006) | NLP | | × | Minimise network travelled time | Hierarchical decomposition | General | Barcelona, Spain |
| Yi and Özdamar (2007) | MILP | × | | Minimise total unsatisfied demand<br>Minimise total lost evacuees | Heuristic algorithm | Earthquake | Istanbul, Turkey |
| Mastrogiannidou et al. (2009) | Meso-Sim | × | | Minimise travelled distance | Heuristic algorithm | General | Port Newark, NJ, USA |
| He et al. (2009) | MILP | | × | Minimise entire network evacuation time | Hybrid Meta heuristics | General | Gulfport, MS, USA |
| Rui et al. (2009) | MILP | × | | Minimise entire network evacuation time | Hybrid Genetic algorithm | General | Gulfport, MS,USA |
| Chen and Chou (2009) | NLP | × | | Minimise travelled costs | Simulation | General | Maryland, USA |
| Sayyady and Eksioglu (2010) | MILP | × | | Minimise evacuation time and casualties | Tabu search heuristic | Hurricane | Fort Worth, TX, USA |
| Chan (2010) | ILP | × | | Maximise number of transferred evacuees | Tabu search heuristic | General | Tucson, AZ, USA |
| Zhang et al. (2010) | MILP | × | | Minimise entire evacuation time | Exact solution | General | Beijing, China |
| Abdelgawad and Abdulhai (2011) | MILP | × | | Minimise travelled time and waiting time | Constraint programming | General | Toronto, Canada |
| Bish (2011) | MILP | × | | Minimise entire network evacuation time | Heuristic algorithm | General | Numerical example |
| Chen et al. (2011a) | MILP | × | | Minimise entire evacuation time | Hybrid Meta heuristics | General | Beijing, China |
| Kaisar et al. (2012) | ILP | × | | Maximise number of transferred evacuees | Microscopic simulation | Hurricane | Washington D.C |
| Goerigk et al. (2013) | MILP | × | | Minimise last group departure time | Exact algorithm (B & B) | General | Numerical example |
| An et al. (2013) | MILP | × | | Minimise waiting, boarding and travel time | Exact solution | General | Mississippi, USA |
| Kulshrestha et al. (2014) | MILP | | × | Minimise entire network evacuation time | Tabu search heuristic | General | Sioux Falls, SD, USA |
| Goerigk and Grün (2014) | MILP | | × | Minimise entire network evacuation time | Iterative heuristic | General | Kaiserlatern, Germany |
| Zheng (2014) | MILP | × | | Minimise the exposed casualty time | Exact algorithm (L.R.) | General | Numerical example |
| Zhang and Chang (2014) | MILP | × | | Minimise last arriving time at shelters | Exact solution | Terrorism | Baltimore, USA |
| Shahparvari et al. (2015a) | MILP | × | | Maximise transferred evacuees, risk<br>Minimise assigned vehicles | Heuristic algorithm | Bushfire | Lake Eildon, Melb, Aus |
| Pourrahmani et al. (2015) | ILP | × | | Minimise the total travelled time | S.A. heuristic | Earthquake | Tehran, Iran |
| Shahparvari et al. (2016a) | MILP | × | | Maximise transferred evacuees, risk<br>Minimise assigned resources | Epsilon constraint | Bushfire | Murrindindi, Melb, Aus |
| Qazi et al. (2016) | MILP | | × | Minimise travelled time | Exact solution | Flood | Kawajima town, Japan |

## Chapter 3

# Research methodology

## 3.1 Introduction

This chapter describes the methodology used in this research for modelling and solving the short-notice bushfire evacuation problem. This chapter begins with a detailed description of the study context which is the Murrindindi area located in Victoria, Australia and highlights its existing challenges. The next section proposes the methodological framework of the bushfire evacuation plans. This is followed by a discussion on the methodological considerations of the research which mainly focuses on the type of data and the data collection procedures. A range of quantitative methodological approaches are discussed in terms of their choices and the steps involved in the formulations of the problem. A discussion on the procedures to solve the proposed models is also provided. The chapter concludes with the summary of the research approaches and procedures used in the research.

## 3.2 Case study context

The Shire of Murrindindi is located approximately 100 kilometres northeast of Melbourne in Victoria, Australia. It contain an area of 3,889 square kilometres. At the 2011 Census, the Shire had a population of 41,860 with a population density of 3.5 people per square kilometre. There are 42 townships with the major towns of Alexandra, Buxton, Eildon, Flowerdale, Kinglake, Marysville, Molesworth, Strath Creek, Taggerty, Yarck, and Yea. 46 per cent of the total land area of the Municipality is forest (1,788 square kilometres), which includes State Forest, Parks and Reserves and another public land. A large proportion of this land is mountainous and densely forested (Figure 3.1). Mitchell Shire is the western neighbour of Murrindindi Shire and is another bushfire-prone area that covers 2,864 kilometres and contains 14 major townships with a population of 34,637.

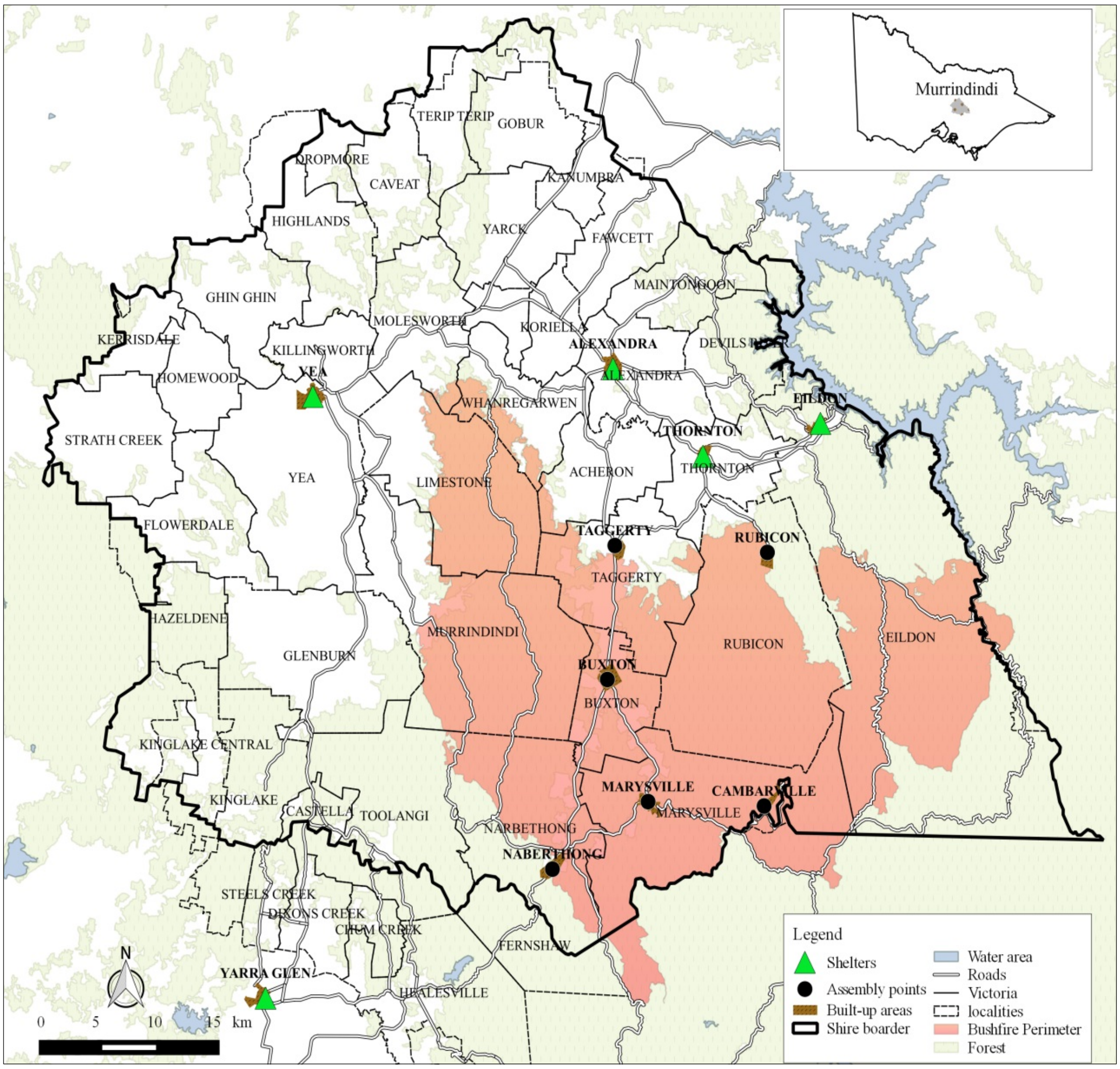



Figure 3.1 Case study region- Murrindindi Shire, Victoria, Australia (source: Victorian Bushfires Royal Commission (2010)).

Over the past decades, the north-eastern part of Victoria State has been classified as a high-risk bushfire prone area and has experienced various massive and minor bushfires resulting in significant losses of land, wildlife, infrastructure and human lives (Teague et al., 2009). This region includes the two Victorian shires of Murrindindi and Mitchell. The Kinglake bushfire was part of the very large 2009 Black Saturday bushfires and included the Kinglake area. 141 deaths and the burning more than 40 per cent of the both shire areas (Victorian Bushfires Royal Commission (2010) resulted (Figure 3.2).

Due to high number of bushfire incidents that occurred in this area, including the majority of the shires townships, this regions will be used as the study area for this research. In the 2009 Black Saturday bushfires, two separate massive bushfires merged into the Kinglake Complex bushfire (Fig 3.2). The first started from the township of Kilmore to the west at around 11:55 pm on 7 Feb and the Murrindindi bushfire started on the same day at 15:00 pm near Murrindindi township. On the day after they merged and created the Kinglake complex bushfire. The Kinglake Complex bushfire affected 78 townships and displaced an estimated 7,562 people. (Figure 3.2)

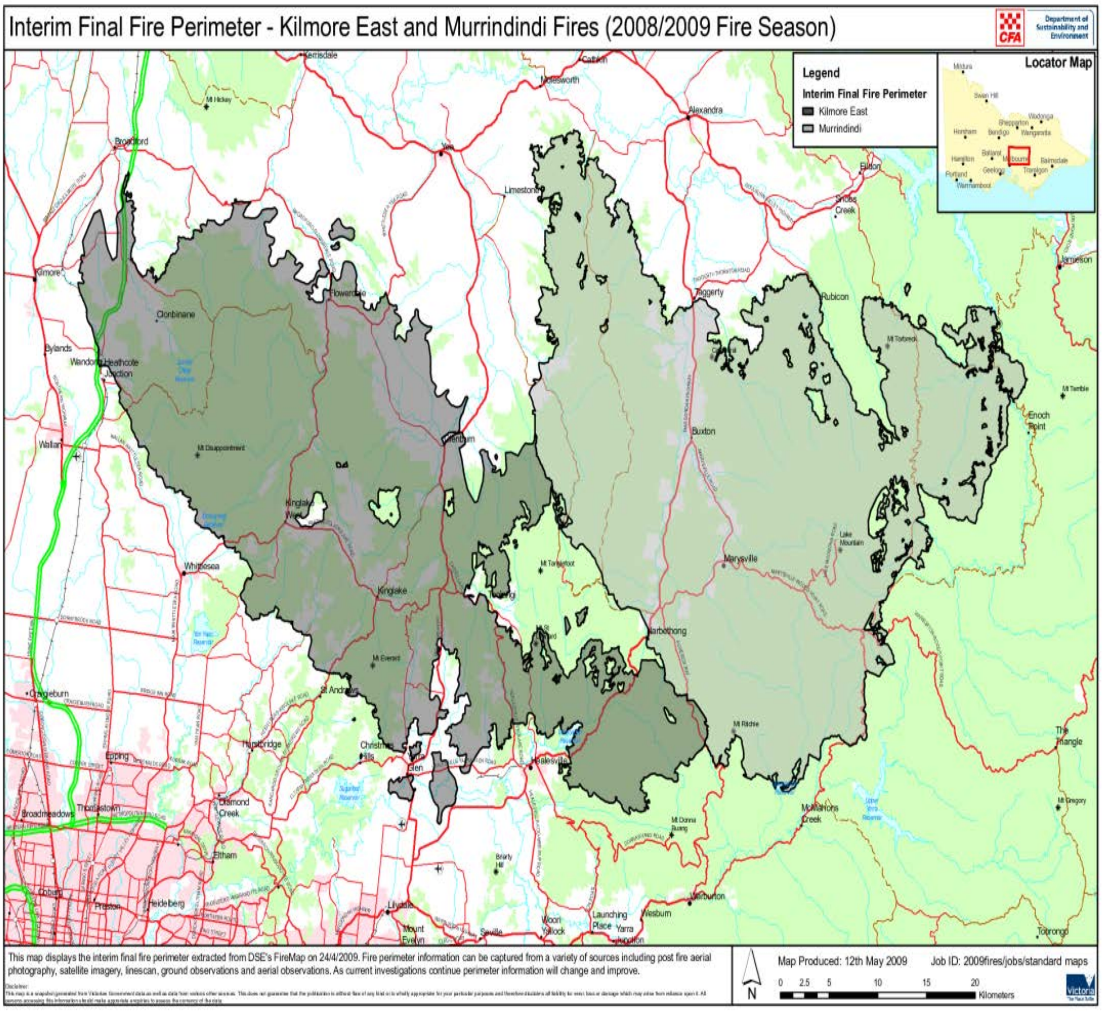



Figure 3.2 Black Saturday Kinglake complex Bushfire Map (source: CFA (2010))

These two Shires then experienced a series of bushfires on 7 February 2009, Black Saturday, with the first fire starting north of a saw mill in Wilhelmina Falls Road in Murrindindi at approximately 2:55 pm. The bushfire traversed rapidly and by 4:30 pm it reached Narbethong, a distance of more than 50 kilometres. Following a wind change that occurred at approximately 6:15 pm, the fire then swept through the communities of Marysville, Buxton, and Taggerty. The bushfires burnt 168,542 hectares of land (40 of the shire) and disrupted Melbourne’s water reservoirs. The Murrindindi bushfire resulted in 40 deaths, 71 casualties, and the evacuation of more than 500 people, mainly in the areas of Marysville, Narbethong, and Buxton (Figure 3.3). Much of the town public infrastructure including the police station, primary school, kindergarten, and health clinic were also burned down.

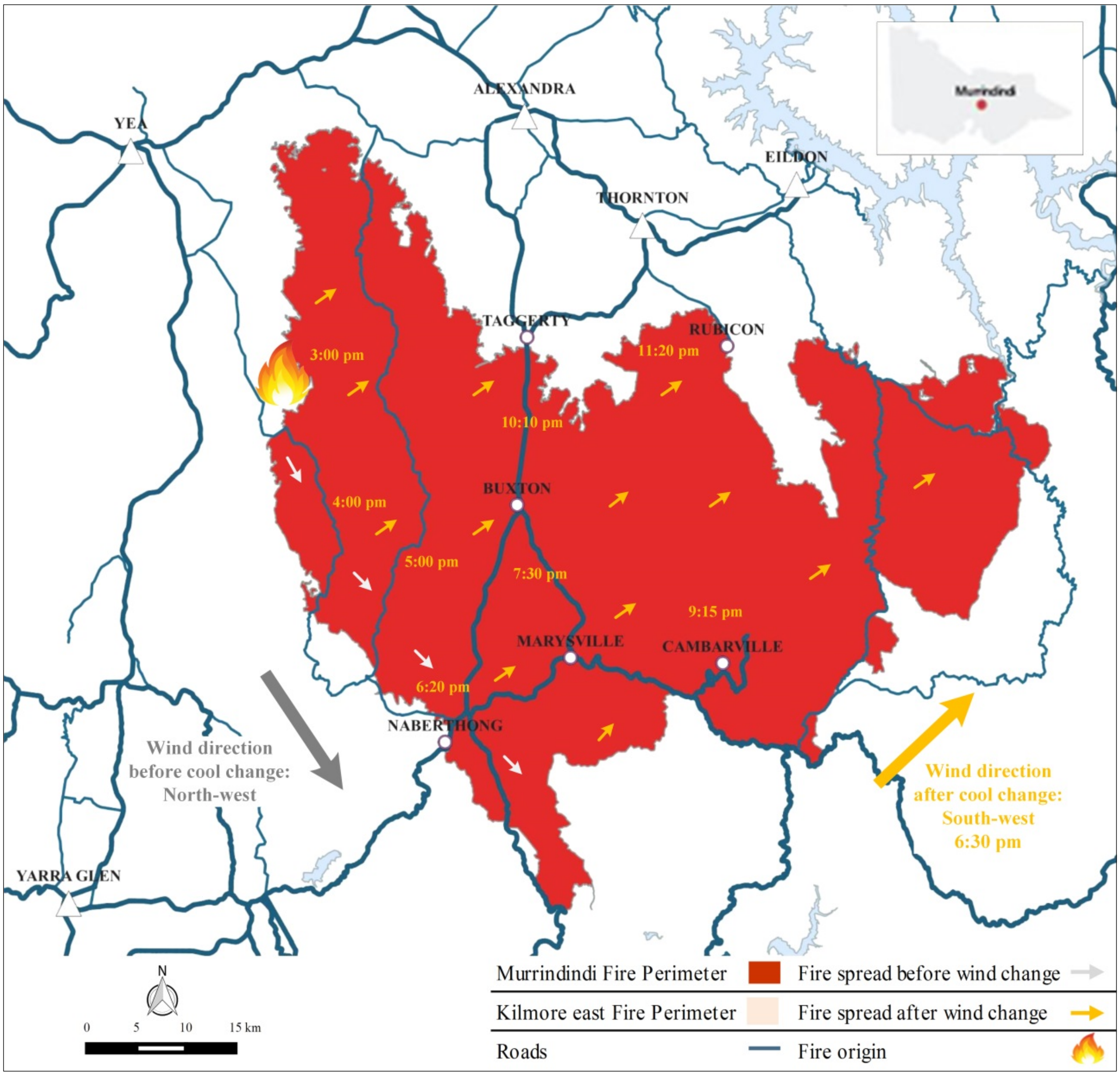



Figure 3.3 Murrindindi 2009 Black Saturday bushfire propagation map (source: Victorian Bushfires Royal Commission (2010)).

As it is shown in Figure 3.3, the fire ignited on the north-western side of the area adjacent to the Murrindindi Sawmill at approximately 2:55 pm. The grey and yellow arrows show the wind direction on Black Saturday. The white and yellow arrows respectively show bushfire direction before and after the wind direction change that occurred at approximately 6:30 pm. After around 9 hours, the fire reached nearby Rubicon.

Table 3.1 summarises the fatalities, sources of the ignition of the fires and what was destroyed in those particular bushfires in this region.

Table 3.1 Summary of the 2009 Black Saturday bushfires damages by locality (source: Victorian Bushfires Royal Commission (2010))

| **Area** | **Area(ha)** | **Fatalities** | **Destructions** | **Ignition source** | **Fire name/origin** |
|---|---|---|---|---|---|
| Kinglake Area | 180,000+ | 120 | 1,244 houses | Power lines | Kilmore East fire |
| Marysville Area | 150,000+ | 39 | 590 houses | Unknown | Murrindindi Mill fire |
| Central Gippsland | 32,860+ | 11 | 247 houses | Arson | Churchill-Jeeralang fire |
| Beechworth | 30,000+ | 2 | 29 houses | Power lines | Mudgegonga fire |
| Bunyip State Park | 24,500 | 0 | 24 houses | Arson | Bunyip State Park fire |
| Wilsons Prom | 11,000+ | 0 | - | Lightning | Wilsons Prom |
| Redesdale | 10,000 | 0 | 12 houses | Unknown | Redesdale |
| Horsham | 5,700 | 0 | 8 houses | Power lines | Remlaw fire |
| Weerite | 1,300 | 0 | 10 houses | Power lines | Weerite |
| Coleraine | 770 | 0 | 1 house | Power lines | Coleraine |
| Maroondah | 505 | 0 | - | Spotting | Maroondah complex |
| Bendigo | 384 | 1 | 61 houses | Arson | Maiden Gully |
| Dandenong Range | 5+ | 0 | 9+ houses | Unknown | Upper Ferntree Gully fire |
| Totals | 450,000+ | 173 | 2,029+ | | |

To frame a real base for testing solutions developed using operations research approaches in this research, this study, therefore, will analyse the Marysville bushfire as a case study.

## 3.3 Methodological framework

This research aims to develop optimisation models to enhance emergency responses to short-notice bushfire emergency evacuation under different disruption scenarios. To achieve this, two main objectives are defined and formulated: maximisation of number of evacuated people from affected areas to safer places, and minimisation of number of allocated resources (shelters and vehicles) via safest routes. The solutions created will be then tested using data from the bushfire scenario described in section 3.2 above. To develop and evaluate solutions a four step process is used to identify an evacuation planning procedure that meets the objectives stated above.

### 3.3.1 Planning procedure

**Step 1: Evaluating community response to protective actions**

Using the analysis of household preparedness and response survey data (Whittaker et al., 2013), step 1 will evaluate the community's response to protective actions to identify and estimate the range of bushfire affected people who want to shelter in place and those who are required to shelter in a refuge. Consequently, determination of demographic characteristics such as the size of the population at risk and characteristics of the affected population for each zone will be identified at this stage to be utilised as an input data for next stages. The results of this stage will be analysed to estimate how many people prefer to leave early and how many prefer to stay and protect their properties.

**Step 2: Determination of potential shelters, available routes and**

The step two identifies the potential places suitable to be designated as safe shelters. Known public areas such as ovals, Parks, and CFA (Country of Fire Authority)[3] centres are currently identified by the CFA as safe areas (evacuation point) to assemble there. CFA defined neighbourhood safer places out of the bushfire affected areas are used as designated shelters in this research. Available routes and functioning shelters also will be estimated in this step. This will be determined on the basis of certain specifications such as capacity, distance, and road accessibility. In addition, the clearance time (i.e. time window) for each affected area will be estimated.

**Stage 3: Selection of optimal shelters, routes**

By utilisation the locating-assigning models, this stage will optimally assign shelters, safest routes, required rescue vehicles to maximise the coverage of number of transferred evacuees in each bushfire propagation scenarios. The risk of disruption for each link is considered in this section. The risk data are derived from VicRoads bushfire risk assessment (VicRoads, 2013). The accessibility of each shelter is also considered by considering time window for the connection links. In this research, it is assumed that once a route is disrupted, the connected shelter is no longer available.

[3] CFA (Country Fire Authority) is a volunteer and community based firefighting and emergency services organisation in Victoria State, Australia.

**Stage 4: Computing optimal evacuation routes**

This step will use a routing problem solution approach to find optimal routes for short-notice evacuation. This stage will identify the roads expected to be heavily used during the evacuation as well as their characteristics such as the capacity, traffic and disruption risk. Also, the number of trips and the number of vehicles required to evacuate affected people and required clearance times in different scenarios will be calculated and analysed.

### 3.3.2 Expected outputs

The adopted research methodology will generate the following outputs, respectively:

- The number of evacuees at each evacuation point which are transferred by each vehicle under each scenario.
- The selection of optimal shelters and hubs between potential places (aiming to maximum coverage to evacuate affected people).
- The selection of the optimal route(s) to reach the evacuation points and evacuate people to shelters under each scenario.
- The number of vehicles which will be used for evacuation under each scenario.
- The schedule of evacuation of each vehicle in each time window.

## *3.4 Data*

The data required for this research are classified as follows:

### 3.4.1 Geographical and Demographical data

The study area compromises six main townships under fire risk, including Narbethong ($i_1$), Marysville ($i_2$), Taggerty ($i_3$), Buxton ($i_4$), Cambarville($i_5$), and Rubicon ($i_6$) (Figure 3.4). The townships are created as point file with x and y coordinates.

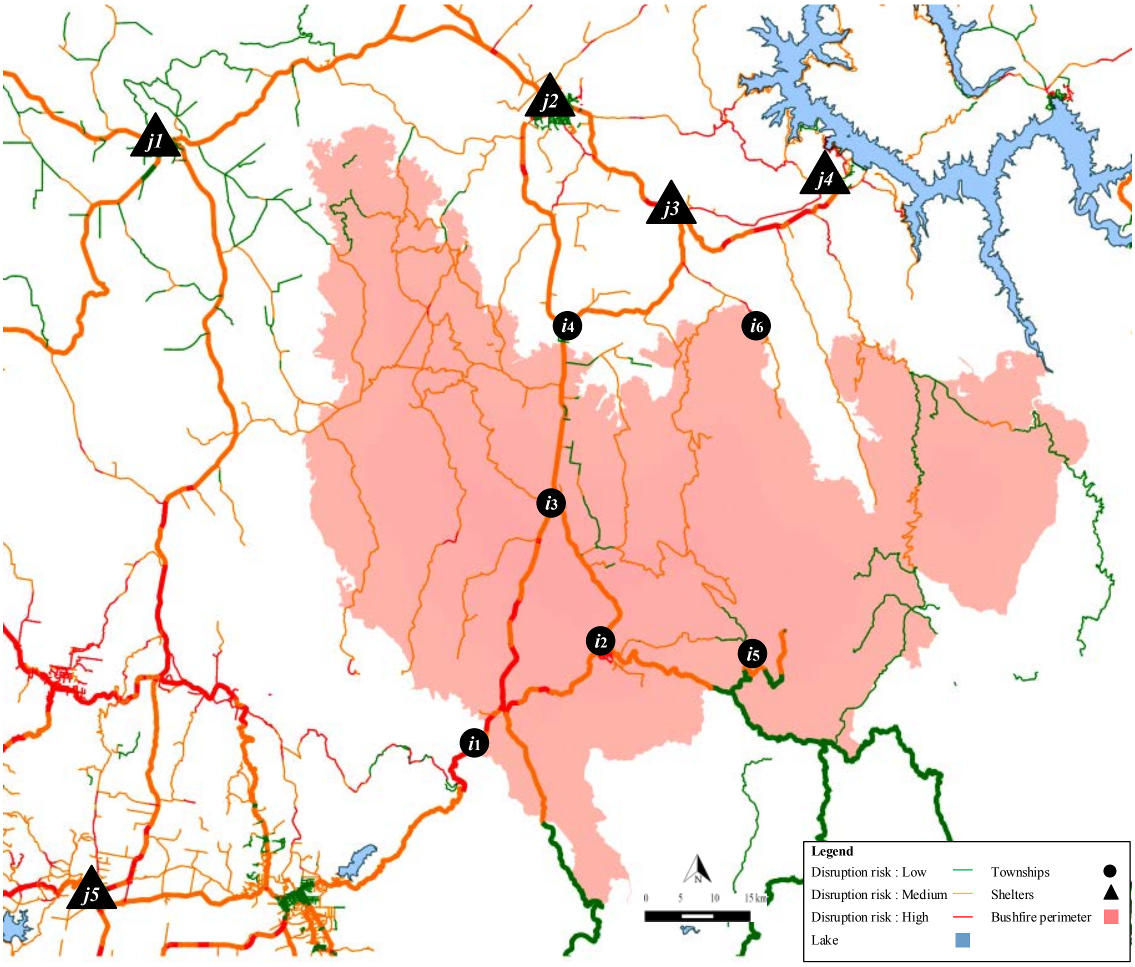



Figure 3.4 Location of the affected townships and shelters in the case study area.

The population load across the demand nodes (townships) is estimated using the 2011 census data. Approximately 2,160 people (Table 3.2) were to be evacuated from major townships in the Black Saturday fires. Approximately one-half (51 per cent) of residents affected by the Black Saturday bushfires were classified as late or very late evacuees (Whittaker et al., 2009). In this research, it is assumed that the number of late evacuees is half of the population of the affected townships, which is approximately 1,100 (Table 3.3)[4]. The disaggregate population load is linked to point data as an attribute.

[4] The real resident population of hazardous townships is gained from ABS, A. B. S. 2011. Canberra. Australian Bureau of Statistics.

Table 3.2 Demographical information of the case study area (source: ABS (2011))

| Affected Townships | Population | Families | Private dwelling | Vehicle per Private Dwelling Carless | One | Two | Three+ | Average | Age Median | Children (0-14) | Old (65+) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Narbethong | 474 | 130 | 288 | 5.8% | 24.6% | 38.0% | 31.6% | 2.2 | 47 | 15.6% | 17.8% |
| Marysville | 518 | 143 | 192 | 3.5% | 34.3% | 43.3% | 18.9% | 1.8 | 51 | 15.9% | 27.7% |
| Taggerty | 330 | 91 | 226 | 7.2% | 29.3% | 41.4% | 22.1% | 2.1 | 53 | 15.7% | 19.3% |
| Buxton | 257 | 64 | 161 | 6.5% | 28.3% | 48.4% | 16.8% | 1.9 | 45 | 13.6% | 23.7% |
| Cambarville | 220 | 50 | 141 | 4.5% | 39.3% | 36.0% | 20.2% | 1.8 | 40 | 18.0% | 8.6% |
| Rubicon | 361 | 99 | 225 | 8.2% | 36.7% | 38.8% | 16.3% | 1.9 | 51 | 17.4% | 26.8% |
| Total | 2160 | 577 | 1233 | 5.95% | 32.08% | 40.98% | 20.98% | 1.95 | 48 | 16.03% | 20.65% |

Five shelters in adjacent townships (destinations) are nominated by Country Fire Authority (CFA) as safe refuge (CFA, 2014). They are Goughs Bay Fire Station in Alexandra($j_1$), a recreation reserve oval in Thornton($j_2$), a basketball court in Eildon($j_3$), a skate park in Yea($j_4$), and a racecourse track in Yarra Glen ($j_5$) (Figure 3.4). Shelters are identified on a wide range of criteria, including capacity, accessibility, vulnerability and availability (CFA, 2014). Each shelter has a specific capacity and associated constraints as accessibility and availability to safely shelter evacuees (Table 3.3). These shelters are also generated as point data with attributes assigned to each of the individual shelter.

Table 3.3 Case study population and capacity data

| | Assembly points | Population | Time Windows | | Shelters | Capacity |
|---|---|---|---|---|---|---|
| $i_1$ | Narbethong | 240 | 130 | $j_1$ | Alexandra | 1500 |
| $i_2$ | Marysville | 260 | 190 | $j_2$ | Thornton | 500 |
| $i_3$ | Taggerty | 170 | 240 | $j_3$ | Eildon | 500 |
| $i_4$ | Buxton | 130 | 300 | $j_4$ | Yea | 1000 |
| $i_5$ | Cambarville | 110 | 360 | $j_5$ | Yarra Glen | 1000 |
| $i_6$ | Rubicon | 190 | 400 | | | |

### 3.4.2 Route reliability (disruption risk) data

In geographically dispersed areas such as the region being studied there might be $k$ different routes between assembly point $i$ and the selected shelter $j$. Furthermore, as depicted in Figure 3.5, each route may contain several segments that can be denoted as $K_{1,5,1} = \{l_{24} - l_{25}\}$, …, $K_{1,5,2} = \{l_{20} - l_{17} - l_{16} - l_{14}\}$, …, $K_{i,j,k} = \{l_i - \cdots - l_o - \cdots - l_k\}$.

Each evacuation plan (EP) may include a set of optimal progress routes and can be denoted as $EP_i = \{K_{i,1,1}, R_{i,1,2}, \ldots, R_{i,j,k}\}$ (Table A1, Appendix). In this research, the VicRoads[5] bushfire risk assessments are adapted as the source for determining the disruption risk for each route (Table A2, Appendix). Each segment in each route has a specific risk of disruption as indicatively measured by VicRoads (VicRoads, 2013) (Table 3.4).

Table 3.4 Bushfire routes risk prioritisation module (source: VicRoads (2013))

| | | | | | | |
|---|---|---|---|---|---|---|
| **Risk** 100% $(IP_l \times PP_l \times RRC_l \times LC_l)$ | $(IP_l \times PP_l)$ Probability | 50% | $IP_l$ (Ignition Probability) | 45% | Ignition potential | 50% |
| | | | | | Fuel on road reserve | 20% |
| | | | | | Ignition history | 30% |
| | | | $PP_l$ (Propagation Probability) | 55% | Fire Behaviour | 50% |
| | | | | | Propagation ability | 50% |
| | $(RRC_l \times LC_l)$ Consequence | 50% | $RRC_l$ (Road Reserve Consequence) | 10% | Economic assets | 40% |
| | | | | | Cultural assets | 5% |
| | | | | | Environmental assets | 5% |
| | | | | | CFA precincts | 5% |
| | | | $LC_l$ (Landscape Consequence) | 90% | Economic assets | 40% |
| | | | | | Cultural assets | 10% |
| | | | | | Environmental assets | 10% |
| | | | | | Human assets | 50% |

From Table 3.4, risk of each segment is calculated by the following equation:

$$(IP_l \times PP_l) \times (RRC_l \times LC_l) = R_l\% \qquad \forall\, l \in \qquad (3.1)$$

where:

$IP_l$ is the probability of ignition;

$PP_l$ is the Probability of propagation beyond the road reserve of section $l^{\text{th}}$ in route $k^{th}$

$RRC_l$ is the consequence of fire burning on the road reserve of section $l^{\text{th}}$ in route $k^{th}$

$LC_l$ is the consequence of fire burning in the wider landscape of section $l^{\text{th}}$ in route $k^{th}$

$R_l\%$ is the risk rating assigned of section $l^{\text{th}}$ in route $k^{th}$.

The output of the risk assessment is illustrated by the application of a standard deviation approach to the classification of risk levels. Figure 3.5 classifies the disruption risk into three groups based on the level of risk: low-risk roads (marked in green), moderate-risk roads (marked in orange), and high-risk roads (marked in red).

[5] VicRoads (or Roads Corporation of Victoria) is a statutory corporation which is the road and traffic authority in the state of Victoria, Australia. VicRoads plans, develops and manages the arterial road network and delivers road safety initiatives and customer focused registration and licensing services.

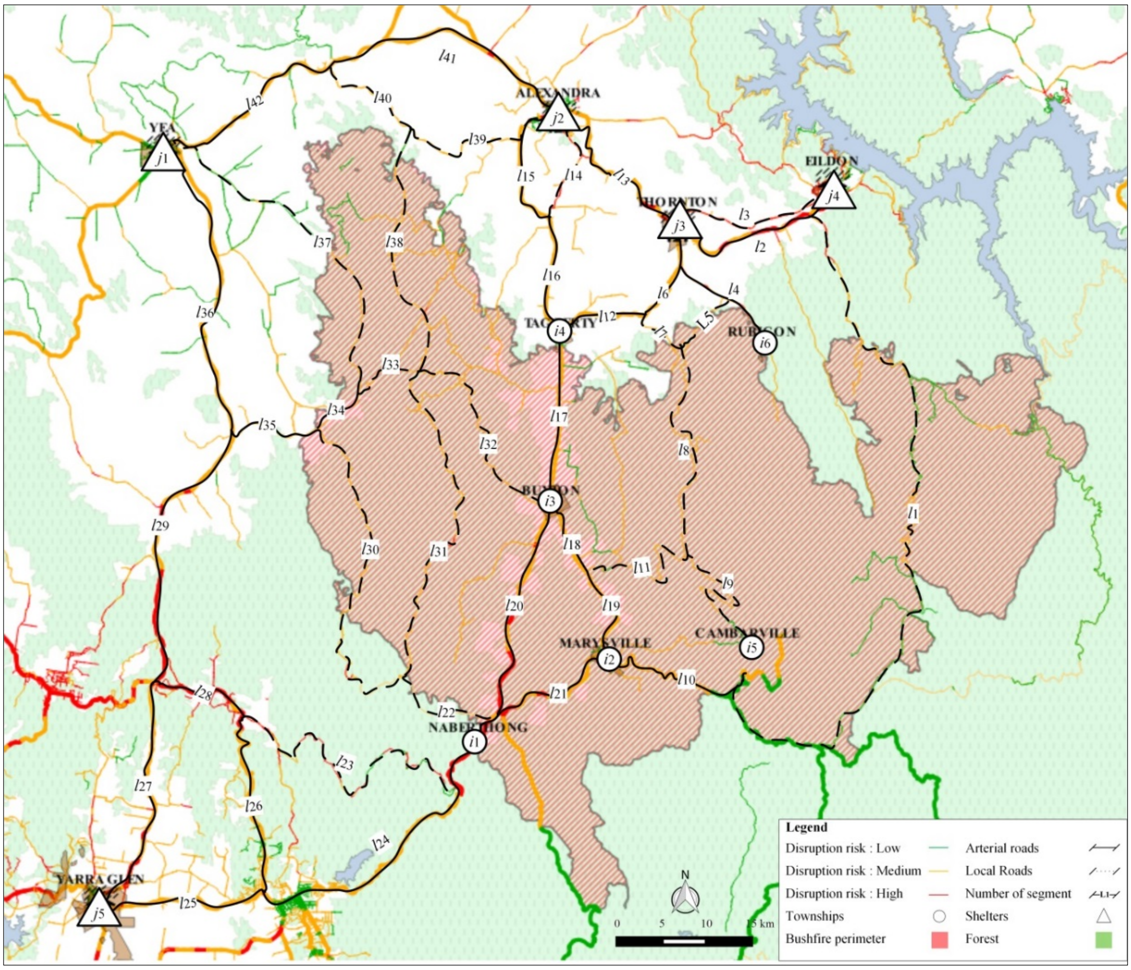



Figure 3.5 An overlay of the transportation network with the disruption risk map for the bushfire-affected Murrindindi Shire area on Black Saturday.

In Figure 3.5, each road between the townships contains several segments that are indicated by dashed lines and numbered with an index of "*l*". The arterial roads are numbered in the same manner and are highlighted by bold black lines. The disruption risks of routes are marked in three colours. Red indicates a high-disruption risk, while orange and green respectively denote medium- and low- disruption risks.

Based on the length of each road segment, the weighted average sum method is applied to calculate the cumulative risk of routes as follows:

$$\bar{\mu}_{ijk} = \frac{\sum_{l=1}^{L}\left(\mu_l \times D_l\right)}{\sum_{l=1}^{L} D_l} \qquad \forall i \in I, j \in J, k \in K \qquad (3.2)$$

Where $\bar{\mu}_{ijk}$ denotes the average capacity of route *k* for vehicle type *v*, $\mu_l$ denotes the risk rating assigned to section *l* in route *k,* and $D_l$ denotes the geometric distance of section *l* in route *k* (Table A2, Appendix).

Next section describes how the route passage capacities are calculated and how the required data are derived for this research.

### 3.4.3 Route passage capacity data

Route passsage capacity determines the maximum number of vehicles that can travel in each segment of a given route. Route passage capacity plays a key role in the efficient distribution of vehicles to prevent traffic congestion as it affects the speed and volume of vehicles. Evacuation plans must consider transportation network capacity constraints. It should incorporate the use of passenger vehicles and transit buses to enhance the efficiency of emergency response (Cox, 2006). In this research, the weighted sum method is used to precisely evaluate passage capacity of the transportation routes as expressed in equation $(3.3)$ below:

$$\bar{\lambda}_{ijk}^{v} = \frac{\sum_{l=1}^{L}\left(\lambda_l^{v} \times D_l\right)}{\sum_{l=1}^{L} D_l} \qquad \forall v \in V, k \in K \qquad (3.3)$$

Where $\bar{\lambda}_{ijk}^{v}$ represents the average capacity of route *k* for vehicle type *v*, $\lambda_l^{v}$ is the previously predicted capacity of section *l* of route *k* for vehicle *v*, and $D_l$ denotes the geometric distance of section *l* for route *k.* In the calculation of overlapping routes capacity, the minimum capacity of the route with overlapping segments is considered for all the common routes (Table A2, Appendix).

Travel times and traffic congestion are also important consideration in short-notice bushfire evacuation. The data obtained and the methods employed for the analysis are explained in the next section.

### 3.4.4 Travel times and traffic congestion data

Route travel time and rescue vehicle passenger capacity are critical factors in emergency evacuation, which could have significant impact on the performance of time-space networks (Shahparvari et al., 2016a, Shahparvari et al., 2015d). Travel time and rescue vehicle capacity between any two nodes on the network are derived from geographical data and speed zone maps (VicRoads, 2014). These parameters are inputs into the route reliability and passage capability. The VicRoads speed zones map indicates that the maximal travel speed allowed on major roads in the region is 100 kilometres per hour (VicRoads, 2014).

During an emergency evacuation, timing is found to be one of the critical factors (Shahparvari et al., 2016a, Abdelgawad and Abdulhai, 2011). The travel time increases with an increase in traffic. This, in turn, may slow down the evacuation process (Zhao et al., 2010a). There is a wide range of road congestion modules which can be utilised (for example see (Sisiopiku et al., 2004, Han and Yuan, 2005) to tackle different levels of road traffic in evacuation modelling. An appropriate route resistance function, for instance, reflects the resistance to traffic flow across various transit components that may direct or indirectly affect evacuation (Shahparvari et al., 2016a). The following formulation is therefore applied to calculate the inflation of the time factor:

$$\tau_{ijk} \times (1+T) + DT \tag{3.4}$$

Where $\tau_{ijk}$ denotes travel time of route *k* between assembly point *i* and shelter *j*, T defines per cent time inflation of trips due to road congestions (time impedance factor) and *DT* represents the dwell time. *DT* consists of the time lost before opening and after closing the transit vehicle doors, and the time required for boarding\alighting of passengers at heavily used doors. Factors affecting the calculation of dwell times include vehicle floor height and platform height, number of boarding/alighting channels (doors), and fare type and fare collection. Vuchic (2005) developed a formulation to calculate the dwell time (Equation 3.5):

$$\begin{aligned} DT &= t_o + b'\omega_b + a'\omega_a \\ b' &= (b_i / n') \times \Omega_b \end{aligned} \tag{3.5}$$

Where $t_o$ denotes the time lost before/after doors are opened. $b'$ denotes the number of boarding riders through the most heavily used boarding door. $a'$ is the number of alighting riders through the most heavily used alighting door. $\omega_b$ defines boarding times per person. $\omega_a$ denotes alighting times per person. $n'$ represents the number of doors per vehicle and $\Omega_b$ is a coefficient of distribution among doors. It should be noted that in emergency evacuation cases, fares are not collected; thus, the time spent for boarding and alighting per person should be lower than the standard values. However, due to the chaos coupled with emergency evacuation, $\omega_a$ and $\omega_b$ are assumed to be, at least, equal to the typical values (Shahparvari et al., 2016a). It is noted here that in the case of emergency evacuation, passengers would be either boarding at evacuees' pickup points or alighting at safe destinations. On average, the dwell time (vehicle preparation boarding\alighting of evacuees) takes no longer than 12.5 seconds per person in the emergency evacuation (Kittelson et al., 2003). In this research, it has therefore assumed that *DT* is known and pre-defined. The time impedance parameter is therefore set as 10 per cent for each trip.

### 3.4.5 Time windows

The impact of bushfires varies across various segments of a transport network depending upon the intensity, direction of wind and vulnerability of infrastructure (Shahparvari et al., 2016a). Each segment of a route has a different time window, within which evacuation has to be carried out. Hence, once a fire front hits a road segment, it is assumed that all routes containing the impacted segments will no longer be accessible (e.g. in the following network, a blockage at $l_3$ influences. and can therefore disrupt, all of the egress routes from assembly point $i_2$ to shelters $j_1, j_2$ (see Figure 3.6).

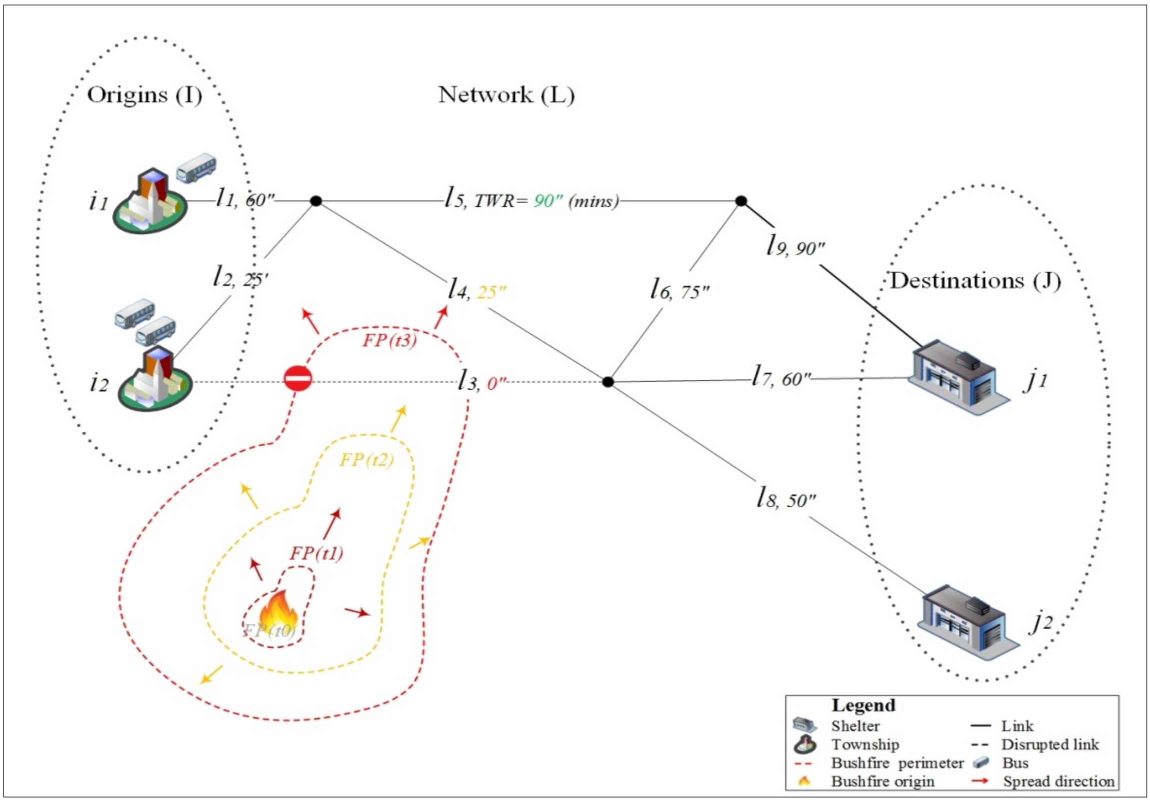



Figure 3.6 Definition of timely impact of bushfire spread on the route segments

The behaviour of bushfire propagation across a geographic area is highly unpredictable (Stepanov and Smith, 2012). In this study, the propagation of the 2009 Black Saturday bushfires is estimated using the historical data provided in the Victorian Bushfires Royal Commission (2010). Therefore, the minimum time window for each segment on a route is considered as the total time window of the route. This is indicated in equation (3.6):

$$TWR_{ijk} = Min\{TWR_l\} \qquad \forall i \in I, j \in J, k \in K, l \in L \qquad (3.6)$$

Where $TWR_{ijk}$ denotes the time window (availability time) of route $k$ between assembly point $i$ and the designated functioning shelter $j$. $TWR_l$ denotes time window of segment $l$ for the same route (Table A2, Appendix).

It is notable that each route has a predefined risk regardless of the designated time window. If the route is assigned to be travelled across, the objective function of the proposed models measures the route reliability (1-risk). Regardless of the route reliability, it can be argued that evacuees can be transferred to shelters only if the route is accessible (i.e. the route has to be completed within the given time window). Even with this assumption, the objective function of the proposed models still maximises the number of transferred evacuees via accessible and reliable routes.

## 3.5 Bushfire disruption scenarios

To implement optimisation models in generating evacuation plans, it is important to develop realistic bushfire scenarios. Three different scenarios are considered in this research to evaluate the effectiveness of the proposed models. The scenarios are developed to reflect varying levels of disruption in different parts of the emergency network. These include the key shelter and the heavily used road segment.

### 3.5.1 Scenario I: baseline

Scenario I reflects the actual series of events that occurred during the 2009 Black Saturday bushfires. The mimicking of the actual event during the bushfire is called the baseline scenario. All the parameters are set based on the derived data that are described in Section 3.4. Origins, destinations, and the regional roads data are derived and incorporated as input parameters for the models. The dynamics of bushfires, the accessibility of roads and time windows for evacuation are all set based on the historical records of the Murrindindi fire (Victorian Bushfires Royal Commission, 2010, CFA, 2010).

### 3.5.2 Scenario II: disruption in a high capacity shelter

Scenario II is created to investigate the ability of the models to generate routing plans under the high capacity shelter disruption. Shelter which accommodates the largest number of late evacuees will be made disrupted to capture the impact of the evacuation plans including vehicle scheduling and utilisation and routing. The likely impact of the potential disruption of the heavily used shelter, which absorbs the highest number of evacuees from the affected areas, will be measured on the evacuation network. This allows the analysis of the impact of an unforeseen disruption to a key shelter.

### 3.5.3 Scenario III: disruption of both highly used roads and shelters

Bushfires have the potential to affect shelter availability as well as route accessibility (An et al., 2013, Shahparvari et al., 2015b). One of the major challenges that emergency evacuation services face during bushfires is the availability and accessibility of critical infrastructure. In the Murrindindi Mill case study, the Maroondah Highway plays a critical role in all routing plans. It is the major route between Buxton and Taggerty the majority of late evacuees are transferred to the northern shelters via this Highway. Police reports expressed doubts over the accessibility of the Maroondah Highway during the 2009 Black Saturday bushfires (Victorian Bushfires Royal Commission, 2010).

The ability of the models to generate routing plans in a scenario of both route and shelter disruption needs to be examined to provide further insights into the extremity of bushfires. Investigations indicate that approximately one-third of the entire late evacuee population during the 2009 Black Saturday transferred to safer places in the northern townships (Victorian Bushfires Royal Commission, 2010). This scenario also assumes that Thornton was not functioning as an available shelter due to unforeseen operational failure. In addition, the Maroondah Highway is assumed to be not accessible due to a major vehicle accident shortly occurred after the bushfire ignited.

## 3.6 Methodology of formulations

As described in the literature review chapter, an optimisation approach is one of the operational research associated methods aiming selection of the best element/decision/option among numerous alternatives. In this research, optimisation methods are used as they allow capturing infrastructure disruptions and its uncertainty. Therefore, the research problem can be modelled as mathematical operational research.

### 3.6.1 Model I (LEBMD-TW): Multi-objective programming

There are various uncertainties, objective functions and constraints in the evacuation problem. Multi-Objective Programming (MOP) is used for evacuation planning, due to multiple conflictive objectives, constraints in road accessibility and the availability of data on the evacuation points, accessibility of reliable routes and shelters. The MOP method has been used in this research as a tool for multiple criteria decision-making problems, simultaneously optimising uncertainty-based problems with multiple constraints and objectives (Andreas and Smith, 2009, Lin et al., 2008, Stepanov and Smith, 2009).

The problem is formulated mathematically as a multi-objective optimisation problem function with a feasible set of decision parameters, objectives and constraints as follows:

$$
\begin{aligned}
&Min\ \left(f_1(x), f_2(x), \ldots, f_k(x)\right) \\
&s.t\ x \in X\ ,
\end{aligned}
\qquad (3.7)
$$

Where X is the set of feasible set of decision vectors and $K \geq 2$ denotes the number of objective functions, $f_k(x)$.

The data of the evacuation network including routing, shelter and vehicle capacity will be used as input in the models to generate a set of final outputs. These outputs will then be analysed for their efficacy and validity as evacuation plans in a variety of bushfire scenarios. Next section describes how the maximum coverage problem module is embedded in the formulation of proposed problem.

#### 3.6.1.1 Maximum coverage problem

Allocating reliable shelters in the evacuation planning is also crucial for an effective evacuation operation. Planning shelter allocation is achieved by adopting the first proposed model of this study, namely LEBMD-TW model. Measuring the average distance travelled to reach each evacuation shelter is a common efficacy measurement approach (Church and ReVelle, 1976). In a real world context, decision-makers may find that they cannot achieve the desired coverage level with their allocated resources. The maximum coverage problem (a special and well-known case of NP-hard problems) thus can be used in this situation to allocate the available shelters to ensure the maximum possible evacuee coverage. This can be represented by the following formula (Megiddo et al., 1983), which is adapted and embedded in the proposed model.

$$
\begin{aligned}
&Maximise \sum_i p_i \gamma_j \\
&s.t. \quad \gamma_i \leq \textstyle\sum_{j \epsilon J} \sigma_j && \forall i \\
&\qquad \textstyle\sum_j \sigma_j \leq \Omega \\
&\qquad \sigma_j,\ \gamma_i \ \epsilon\ \{0,1\} && \forall i, j
\end{aligned}
\qquad (3.8)
$$

Where:

$i$ is the index of assembly points

$j$ is the index of potential shelters

$p_i$ is the late evacuee population at assembly point $i$

$\sigma_j$ is 1 if a shelter is allocated at candidate place $j$, otherwise it is 0

$\gamma_i$ is 1 if evacuees from assembly point $i$ are transported to the dedicated shelter $j$, otherwise it is 0

$\Omega$ is the number of shelters to be allocated.

The next section explains the vehicle routing problem and related variants which are used in the formulation of the second model in this study.

### 3.6.2 Model II (CMDVRP-TW): Vehicle routing problem formulation

Vehicle routing problems (VRPs) are a well-known class of integer-programming problem where a set of vehicle routes must be determined from one or several depots for a number of geographically separated customers or cities (Laporte, 1992). VRPs fall into the category of NP-Hard problems (Lenstra and Kan, 1981). This means that the computational effort needed to solve a VRP increases exponentially with its size. A VRP is a difficult combinatorial problem (Toth and Vigo, 2014). Conceptually it lies at the intersection of two well-documented NP-Hard problems:

- ***The Traveling Salesman Problem (TSP):*** In the multiple traveling salesman problem (MTSP) (Flood, 1956), the capacity of vehicles is infinite. An MTSP can be transformed into an equivalent TSP by adding the number of routes to the graph (k-1, with k representing the number of routes), additional copies of node 0, along with its incident edges (Flood, 1956).
- ***The Bin Packing Problem (BPP):*** The BPP answers whether a feasible solution exists for a VRP (Trong, 1985). The decision version of the BPP is conceptually equivalent to a VRP model where all edge costs are assumed to be zero (i.e. all feasible solutions have an equal cost).

Toth and Vigo (2002) outlined three basic approaches for modelling VRPs that have been proposed in the research literature: v*ehicle flow formulation,* c*ommodity flow formulation* and *set partitioning*. In the v*ehicle flow formulation* approach, binary integer variables are used to show if a vehicle traverses a specific arc or not. This approach is often used for basic VRP models. They are especially useful in cases where the solution's cost can be expressed as the total costs associated with the arcs. However, vehicle flow models cannot deal with many practical issues, such as the situation where a solution's cost depends on the sequence of arcs traversed, or when the cost is dependent on the specific type of vehicle assigned to a specific route.

In the c*ommodity flow formulation* approach, additional integer variables are associated with the arcs. These additional variables represent the flow of commodities along routes travelled by vehicles. These models have been used to generate the exact solutions of capacitated VRPs in some recent studies (Baldacci et al., 2004, Naddef and Rinaldi, 2001).

The decision variables are the feasible routes for vehicles in the third approach to VRP modelling. For each feasible route, these models generate an exponential number of binary variables. The VRP is then formulated as a s*et partitioning* problem where a set of minimum cost routes is selected to serve each customer once while also satisfying any additional constraints. This model allows for extremely general route costs, which is its main advantage (Toth and Vigo, 2014). Route costs can, for example, depend on the sequence of nodes visited, the type of vehicle or they can be non-linear. In addition, the linear relaxation of set partitioning models usually provides a tighter bound than either the vehicle *flow or* c*ommodity flow formulation* models (Toth and Vigo, 2014). However, the set partitioning models usually need the feasible routes to be enumerated. This requires the data for a very large number of variables and the associated extensive pre-processing.

The *vehicle flow based formulation* is the approach used in this study to formulate the VRP model. The following formula is an example of the base case of an incapacitated, multi-vehicle, single depot VRP. The decision variables $x_{ij}^{v}$ are binary, denoting if vehicle v travels from point *i* to point *j*, $x_{ij}^{v} = 1,$ *or not,* $x_{ij}^{v} = 0$.

Minimise $\sum_i \sum_j \sum_v c_{ij} x_{ij}^v$ (3.9)

*Subject to*

$$\sum_i \sum_v x_{ij}^v = 1 \qquad \forall j \qquad (3.10)$$

$$\sum_j \sum_v x_{ij}^v = 1 \qquad \forall i \qquad (3.11)$$

$$\sum_i x_{ip}^v - \sum_j x_{pj}^v = 0 \qquad \forall p \in N, \forall v \qquad (3.12)$$

$$\sum_j x_{0j}^v \leq 1 \qquad \forall v \qquad (3.13)$$

$$x_{ij}^v \in (1,0) \qquad \forall i, j, v \qquad (3.14)$$

$$X \in S \qquad (3.15)$$

Minimising the total travel distance (or cost) by all vehicles is the objective (equation 3.9). Constraints 3.10, 3.11 and 3.12 ensure only one vehicle enters and exits each node. Constraint 3.13 ensures each vehicle only departs the depot once. Constraint 3.14 defines the domain of decision variable of the problem. Sub-tours that do not contain the depot are prohibited (Constraint 3.15).

There are several potential methods of complying with this condition. For example, sub-tour breaking constraints for each vehicle may comprise S. *S* is defined as the union of the $S_v$ sets, as follows:

$$S_v = \left\{ x_{ij}^v : \sum_{i \in Q} \sum_{j \in Q} x_{ij}^v \leq |Q| - 1 \textit{ for all nonempty subset } Q \right\} \qquad (3.16)$$

If each vehicle's capacity is $C_v$ and each customer's demand is $d_i$ units, the capacitated VRP is formulated by adding capacity constraints to the base formulation as follows:

$$\sum_i d_i \left( \sum_j x_{ij}^v \right) \leq C_v \qquad \forall v \qquad (3.17)$$

As discussed earlier in the literature review, several VRP variants can be made by adding constraints to the above VRP formula. Several classic VRP variants are used in this study: capacitated VRP (CVRP), multi-destination VRP (MDVRP), VRP time-window (VRPTW) and dynamic VRP (DVRP). In CVRP, vehicles have a pre-defined capacity limit of the number of passengers they can feasibly carry. MDVRP allows for more than one visit to a destination. VRP-TW adds evacuee time window limitations. In DVRP, elements may be variable, such as the availability of a link over time. The next section explains the research methodology for the formulation of the third model of this research.

### 3.6.3 Model III (P-CMDVRP-TW): Probabilistic (Fuzzy) programming

In recent years, fuzzy programming approaches have been more prevalent due to their ability to directly measure each objective function's satisfaction level. Zimmermann (1978) developed the first fuzzy solution approach for MOLP problems, known as the min–max approach. However, the min-max approach sometimes generates inefficient solutions. To overcome this weakness in solving MOLP problems Sakawa and Yano (1989) proposed a fuzzy interactive that was based on the min–max approach. In addition, Lai and Hwang (1992) also augmented the min–max approach (Section 3.7.4).

A single-phase solution approach for MOLP problems, known as the TH method, was proposed more recently (Torabi and Hassini, 2008) (see Section 3.7.4 for details). This approach was analytically proven to yield efficient solutions. Further, Selim and Ozkarahan (2008) modified Werner and Knowles (1988) aggregation function in proposing their new fuzzy approach for solving MOLP problems.

In this research, an interactive fuzzy solution approach based on the TH method is then applied to solve the proposed possibilitic model.

#### 3.6.3.1 Fuzzification and defuzzification

Fuzzification converts a crisp input variable into fuzzy membership functions (Zadeh, 1990). A fuzzy membership function with corresponding degrees of membership is selected to achieve this fuzzification (Jang et al., 1997). Input variables are assigned into fuzzy sets with membership functions during the fuzzification process. Defuzzification is the inverse operation to the fuzzification process, whereby a fuzzy value is transformed into a crisp value (Buckland, 2005). This process is the required as output needs a crisp value.

### 3.6.3.2 Fuzzy membership function

The characteristic function in fuzzy set theory is called the membership function (MF) associated with fuzzy set A. The membership function is a generalisation of the characteristic function. The MF assigns a real number $\mu_A$ in the interval [0,1], to each element x that is included in this subset A, as shown by the following formula.

$$\mu_A : X \rightarrow [0,1] \tag{3.18}$$

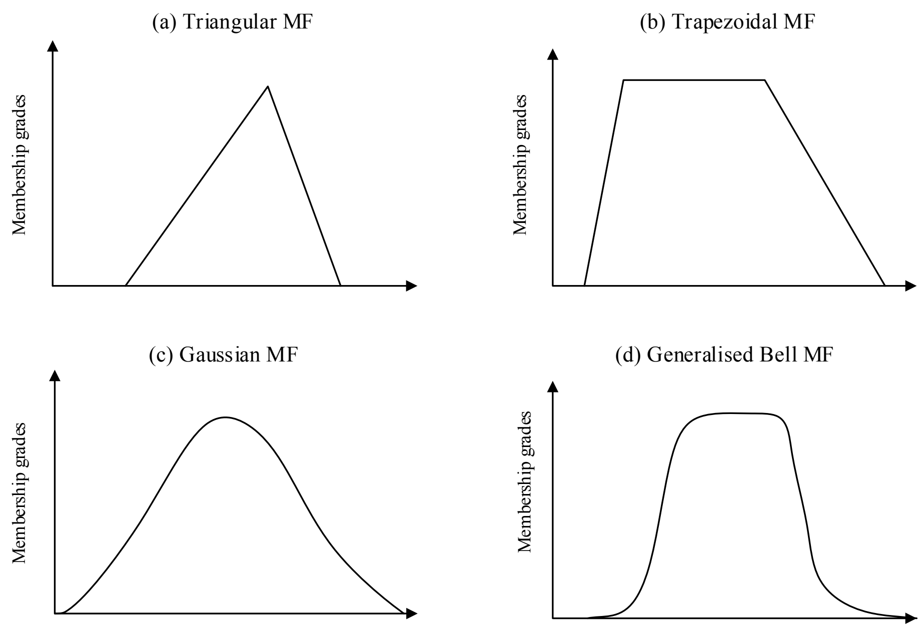



Figure 3.7 Fuzzy Membership Functions: (a) Triangular, (b) Trapezoidal, (c) Gaussian, and (d) Sigmoidal

Figure 3.7 illustrates that both the Bell and Gaussian MFs achieve smoothness. However, they are not asymmetric. The Sigmoidal MF is extremely flexible in specifying fuzzy sets. However, it is unnecessarily complex and is therefore not often used in practice. The Trapezoidal MF represents a range of members whose grades equal 1. Trapezoidal MFs are useful when there are acceptable boundaries of both earliness and lateness in service delivery. A Triangular MF is a special case of a Trapezoidal MF, where only one member has a grade of 1. Triangular MFs have been widely used due to their computational efficiency, especially in real-time applications (Pedrycz, 1994). The following section describes more about triangular fuzzy membership.

### 3.6.3.3 Triangular fuzzy membership

Three parameters $\{a, b, c\}$ specify a Triangular MF, as follows:

$$\mu(x; a, b, c) = \begin{cases} 0 & x \le a \\ \dfrac{x-a}{b-a} & a \le x \le b \\ \dfrac{c-x}{c-b} & b \le x \le c \\ 0 & c \le x \end{cases} \tag{3.19}$$

The point b, with membership grade 1, is called the mean value and a, and c are the left and right hand spreads of *x* respectively. An alternate expression for the above equation, using min and max, is as follows:

$$\mu(x; a, b, c) = \max\left( \min\left( \frac{x-a}{b-a}, \frac{c-x}{c-b} \right), 0 \right) \tag{3.20}$$

The coordinates of x as the three corners of the triangular MF are defined by the three parameters $\{a, b, c\}$ (a < b < c), as illustrated in Figure 3.8 below.

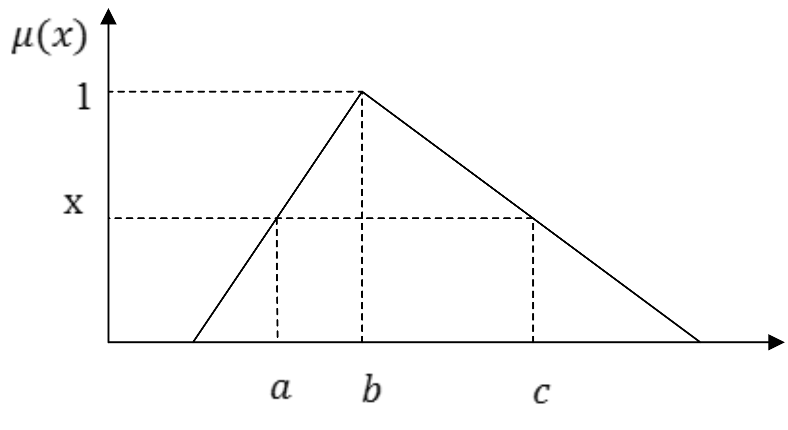



Figure 3.8 Triangular fuzzy membership function

Therefore, considering the triangular fuzzy membership concept, the uncertain parameters of evacuees' population, time windows, travel times and capacities can be converted to fuzzy numbers. An interactive fuzzy solution method then will be applied to solve the possibility model with fuzzy numbers. The solution approaches for each model is explained in the next section.

## 3.7 Methodology of solution approaches

In this research, different optimisation methods are utilised to formulate the problem. The most appropriate solution approach for each formulation is investigated and explained in this section.

### 3.7.1 Model I (LEBMD-TW): Pareto front solutions (epsilon-constraint)

The emergency evacuation problem formulated in this analysis deals with a range of objective functions, uncertainties, and stringent constraints. A number of solution approaches have been developed in operational research for solving multi-objective integer problems (MOIPs). These include goal programming (Wilson and Macleod, 1993), multi- and bi-level programming (Hansen et al., 1992), weighted sum (Scalarising) (Coello Coello and Lechuga, 2002) and Pareto front optimisation approaches *(Zitzler and Thiele, 1998)* such as the lexicographic minimax method (Bazaraa and Goode, 1982) and the epsilon-constraint method (Chankong, 1983).

In goal programming, the goal is typically referred to as a planned objective. The goal programming method measures the deviation of objectives (optimality) from the planned objectives. The objective functions, however, are not simultaneously optimised (Abbass and Sarker, 2002). Multi-level programming is another MOIPs approach that hierarchically orders objectives and successively optimises objective functions. Multi-level programming problems are complex to solve (Hansen et al., 1992) as the last set of objective functions at the bottom of the hierarchy is often constrained, resulting in infeasible conditions. This could mean that the low-level ranked objective functions may have a negligible impact on the derivation of final optimal solution (Vicente et al., 1996).

The weighted sum (scalarising) optimisation method is based on converting multiple objectives to a linear single normalised weighted scalar function, which is often solved by conventional methods. Determining the appropriate weight in this method, however, is challenging. The optimum solution is based on normalisation and the assigned weights (Ehrgott, 2006b).

Overall, despite the broad range of multi-objective optimisation solution methods, multi-objective integer problem solutions are not usually straightforward. Typically, no feasible absolute optimal solution exists to optimise all objective functions concurrently (Ehrgott, 2006a). To address this problem, Pareto-optimal solutions have attracted much more attention, and are often referred to as a ‘‘posteriori’’ or ‘‘non-dominated solution generation’’ (Deb, 2001). Pareto-optimal solutions MOIPs attempt to optimise the main objective by degrading at least one of the other objectives. Out of these, the lexicographic minimax method is one of the most extensively used Pareto optimal solutions to order the weighted average aggregation of objectives. The application of this method is suitable where all of the objective functions are equally important for decision-makers. The key disadvantage of this approach is that some of the results may not be Pareto-optimal because the solution is not typically unique (Kostreva et al., 2004).

The epsilon-constraint method (ε-constraint) is another common general-purpose Pareto front solution approach, which has been widely utilised to solve multi-objective integer problems (Chankong, 1983). This method provides extensive flexibility for decision-makers by varying the lower or upper bounds $\varepsilon_i$ to achieve Pareto optima (Zitzler and Thiele, 1998).

### 3.7.2 Model II(CMDVRP-TW): Heuristic solution approach

Integer programming problems are generally very difficult to solve. Several solution algorithms have been proposed by various researchers (Wolsey, 1998, Benders, 1962, Gomory, 1960, Land and Doig, 1960). Algorithm selection of the best possible approach is important, as some work better on specific problems than others. The characteristics of various algorithms are discussed in this subsection. Integer and combinatorial optimisation algorithms are reviewed in more detail in the integer programming research literature (e.g. Wolsey and Nemhauser (1999)).

The traditional base for integer programming (IP) solution approaches has been linear programming (LP), which was developed in the late 1940s. It quickly became apparent to researchers examining LP that it would be beneficial to solve problems that possessed some integer variables (Dantzig and Ramser, 1959). Algorithms for the solution of pure IP problems were subsequently developed. Dantzig et al. (1954) developed the first, known as cutting-plane algorithms, and these were further developed by Gomory (1963). The branch and bound algorithm was subsequently introduced by Land and Doig (1960). Decomposition (Benders, 1962), implicit enumeration (Balas, 1965), Lagrangian relaxation (Geoffrion, 1974) and heuristic approaches have been used more recently in solving various integer programs. The following general algorithm classifications for integer programming problems were proposed by McCarl and Spreen (1997). Various heuristic algorithms are proposed in the following sections to solve the IP sub-problems in the mathematical model.

#### 3.7.2.1 Cutting-planes

The cutting-plane concept is that the optimal integer point is close to the optimal linear programming (LP) solution, but is not at the constraint intersection, requiring additional constraints to be imposed (Figure 3.9). These were the first formal IP algorithms (Gomory, 1960). Parts of the feasible space are iteratively removed while retaining integer solution points. The additional constraints render the non-integer LP solution infeasible, without any integer solutions being eliminated. This is achieved by adding a constraint requiring the non-basic variables to be greater than a small non-zero value. In its simplest form, a cutting-plane would force the sum of the non-basic variables to be greater than or equal to the fractional part of one of the variables. Such constraints are added by the cutting- plane algorithms until an integer solution is obtained.

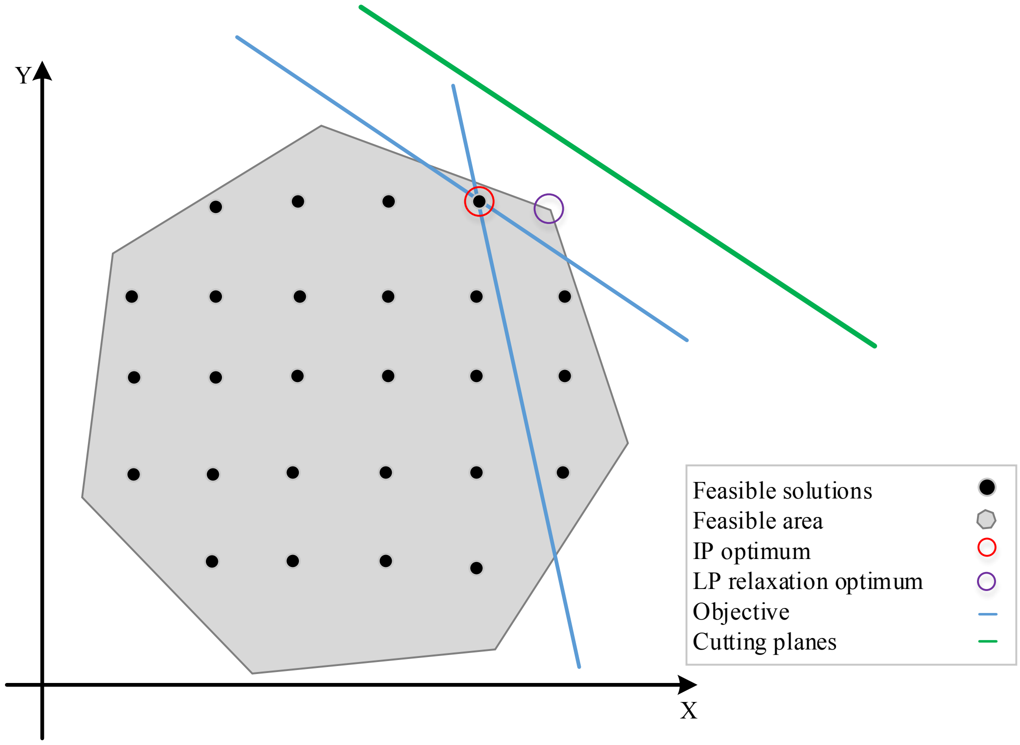



Figure 3.9 Cutting planes in a mixed-integer programming model

Three key points require to be completed regarding cutting-plane approaches. The first is to obtain an integer solution, many cuts may be necessary, often more than can be computationally afforded (Beale, 1965). Second is to find the optimal solution in the first integer solution. It is discovered only after enough cuts have been added. Therefore, the modeller can often be left without an acceptable solution if the solution algorithm runs out of time or space. Third is to decrease the popularity of cutting-plane approaches due to their comparative performance against other algorithms (Beale, 1965).

### 3.7.2.2 Branch and bound

The branch and bound algorithm was the second IP solution approach developed to sovle the IP Problem (Land and Doig, 1960). The algorithm pursues a divide-and-conquer strategy, beginning with an LP solution. Similar to cutting planes, branch and bound algorithms impose constraints that force the LP solution into an integer solution (Figure 3.10). The difference is that branch and bound constraints place upper and lower boundaries on variables (Garfinkel and Nemhauser, 1972).

Two problems (branches) are generated by the branch and bound approach for each LP solution. Each problem forms an increasingly constrained LP problem by excluding the unwanted non-integer solution. Several decisions are required, including which variable to branch and which problem to solve (i.e. which branch to follow). An integer solution may be found by solving a particular problem. However, the optimal integer solution cannot be determined until all problems have been solved either implicitly or explicitly.

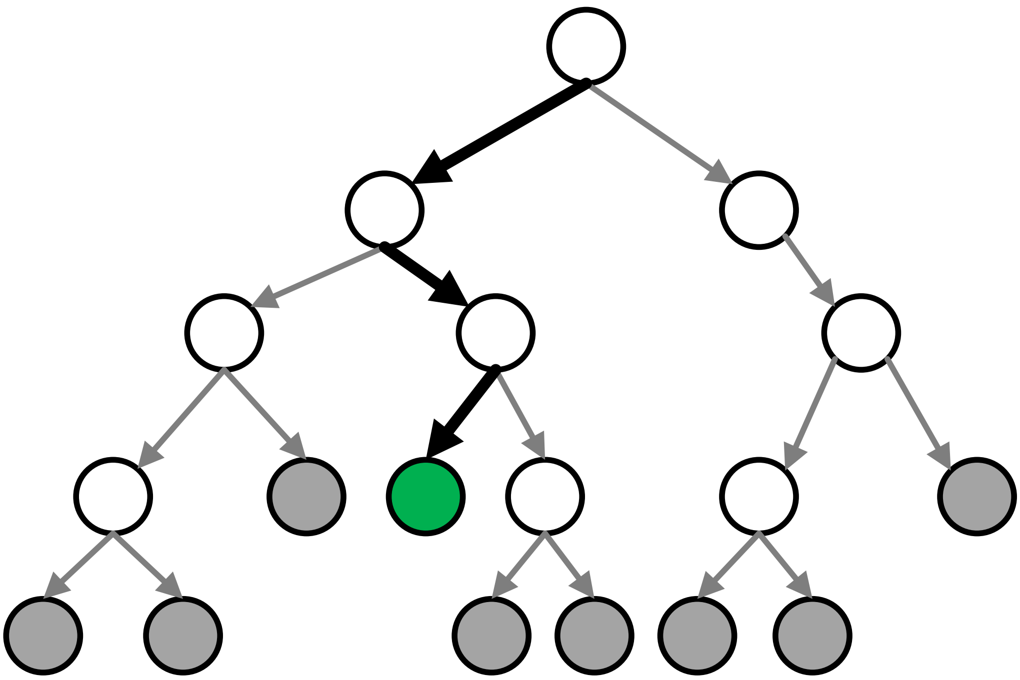


Figure 3.10 Branch and Bound algorithm.

Maximisation problems display decreasing values for the objective function when additional constraints are added. Therefore, when an integer feasible solution is found, any solution with a smaller value for the objective function cannot be optimal, whether it is an integer solution or not. Similarly, further branching on any problem below it cannot yield a better solution. At any stage of the algorithm, the best integer solution found provides a bound that limits the branches (problems) to be searched. As better integer solutions are found, the bound is continually updated (Brusco and Stahl, 2006).

The bounds on the integer variables are the only difference between each problem generated and the parent problem. An LP algorithm that can incorporate changes to the bound can, therefore, conduct branch and bound calculations. The branch and bound solution algorithm is incorporated in many commercial software applications and is the most widely used general purpose IP solution approach (Brusco and Stahl, 2006).

However, the branch and bound algorithm approach can be expensive, because it yields intermediate solutions which although usable, are not optimal (Mohasel Afshar, 2011). It may often generate near-optimal solutions quickly, followed by much time spent verifying the optimal solution.

#### 3.7.2.3 Lagrangian relaxation

Another area of IP algorithm development is the Lagrangian relaxation (Geoffrion, 1974, Fisher, 1981). In this approach, Lagrangian multipliers are used to relax some constraints into the objective function. Difficult constraints are removed from the problem to enable the integer programs to be more easily solved. LP is able to solve IP problems with structures like the transportation problem. The key is choosing the right constraints to relax and developing the Lagrangian multiplier values that will lead to the appropriate solution. This approach is typically used in two domains: 1) to improve the performance of solution bounds, and 2) to develop feasible problem solutions that can be adjusted through heuristics (Fisher, 1981). At any stage, the relaxed Lagrangian problem provides an upper solution bound compared to the un-relaxed problem. Lagrangian relaxation is widely used in branch and bound algorithms to determine upper problem bounds, helping to evaluate whether further branching is worthwhile.

#### 3.7.2.4 Benders decomposition

Benders decomposition is another integer program solution algorithm. It uses structural exploitation to solve mixed-integer programs. Under the procedure developed by Benders (1962), a mixed-integer problem is decomposed into two problems that are solved iteratively; an integer master problem and a linear subproblem.

However, for certain problem structures, the procedure works poorly. For example, when the master problem’s X variables do not yield a feasible subproblem. Convergence is faster the more accurately the master problem’s constraints portray the sub-problem’s conditions. The tighter (i.e., the more constrained) the master problem’s feasible region is, the better. Constraints are entered into the master problem when possible to preclude any feasible but unrealistic (i.e. sub-optimal) problem solutions being generated.

Benders' approach allows a large mixed-integer problem to be decomposed into and a larger simple linear program and a smaller difficult master problem. The problem's solution is generated by two software programs that individually would each be incapable of solving the single large overall problem. It is notable that the master problem is still an integer program that still may prove difficult to solve using the Benders decomposition approach.

#### 3.7.2.5 Structural exploitation

Past IP experiences demonstrate that general-purpose IP algorithms do not solve all IP problems (Mohasel Afshar, 2011). In this approach, the specific problem structure is used to generate the solution algorithm. Both Lagrangian relaxation and Benders decomposition are examples of structural exploitation approaches. Some specialised branch and bound algorithms and problem reformulation approaches are further examples. Structural exploitation can be achieved by developing a specific problem algorithm or, by transforming a problem so that it is easier to solve. The application structural exploitation algorithms have sometimes led to spectacular results. For example, problems containing thousands of variables have been solved in seconds (McCarl and Spreen, 1997). Unfortunately, no existing structural exploitation algorithms solve all IP problems. However, specific types of algorithms are effective in solving IP problems with specific structures.

#### 3.7.2.6 Heuristics

Several IP problems are difficult to solve because of their combinatorial nature. Papadimitrou and Steiglitz (1982) found extreme computational complexity in their study of NP-complete problems such as the traveling salesman problem. These computational difficulties have resulted in a large number of IP heuristics being developed, including some that are specific to certain types of problems as T-counter, origin-based T-counter, Y-list, and Y-list modal heuristics (Mohasel Afshar, 2011). Heuristics perform well on special types of problems, quite often coming up with errors of smaller than two per cent (Fisher, 1981). Heuristics can be used effectively in the following situations (Mohasel Afshar, 2011):

- when data quality does not warrant exact optimal solutions to be generated;
- when a simplified model has been utilised; and/or

- when an exact, reliable method is either, computationally unattractive, not available and/or too expensive.

A heuristic may be used to improve the performance of an optimiser by repeatedly solving the problem, or saving time in branch and bound code. Golden and Assad (1988) reviewed a number of traveling salesman problem heuristics. Zanakis and Evans (1981) provided a general heuristics review, including an analysis of heuristics selection in relation to both other heuristics and other optimising methods.

The mathematical models proposed in Chapter 4 are complex integrated models that incorporate large-scale mixed general IP provide the opportunity for a central operational plan to be developed that allocates limited resources to their best possible use, and eliminates delays. However, solving such comprehensive mathematical models is challenging. Even commercial software applications are incapable of generating the optimal solution within a reasonable time window.

Exact solution algorithms will be incapable of solving the proposed model in this study efficiently, based on an analysis of the solution approaches for similar models that are outlined in the research literature. The best approach, therefore, may be the development of fast heuristic algorithms that are able to generate near-optimal solutions within relatively short time windows. However, given that the model in this study is more complex than those that feature in the research literature, structurally decomposing the problem into smaller or easier problems is likely to be beneficial. The next section provides background and procedure for Meta-heuristic solution approach (Genetic algorithm) that developed in order to evaluate the effectiveness of prosed heurist solution approach in this research.

#### 3.7.2.7 Meta-heuristic solution approach - genetic algorithm

A genetic algorithm (GA) replicates the process of natural selection and evolution. It is a search heuristic that is sometimes called a meta-heuristic (Holland, 1973). It is commonly used for generating useful optimisation and search problem solutions. GA is part of the larger class of evolutionary algorithms (EA). An EA exploits a population of points in parallel, instead of a single point, in order to conduct a solution search. The GA is capable of generating solutions for both unconstrained and constrained optimisation problems.

The GA selects random individuals from the population as parents, using them to produce the next generation's children. The population evolves toward the optimal solution over successive generations. The GA can be applied to solve various optimisation problems where standard optimisation algorithms are not well suited. These problems include those with an objective function that is discontinuous, undifferentiated highly non-linear, or stochastic. The GA is also able to solve problems of mixed-integer programming (MIP), where some components of the problem are restricted to an integer value.

At each step, the GA uses three major rules at each to create the population's next generation (Holland and Reitman, 1977):

- selection rules provide the parents to populate the next generation.
- crossover rules combine two parents to provide the children.
- Mutation rules randomly apply changes to individual parents to provide children.

The GA typically includes the following steps:

- randomly population initialisation (t)
- define the population fitness(t)
- reiteration
- choose parents from the population pool (t)
- apply the crossover rules to parents to create the population (t+1)
- apply the mutation rules to population (t+1)
- define the fitness of the population (t+1)
- iterate until the best output is decent enough.

In this research, a designed genetic algorithm is utilised as an alternative solution approach to compare the performance of the results of proposed heuristic method. The overall developed genetic algorithm for the proposed model is outlined in detail in Chapter 5 - solution approaches. The next section explains the research methodology for the formulation of model under uncertainty in form of possibilistic programming.

## 3.7.3 Model III (P-CMDVRP-TW): Interactive possibilistic programming approach

Several approaches for solving multi-objective linear programming (MOLP) models are outlined in the research literature. These include fuzzy programming, which is an approach that is increasingly being applied. The major advantage of fuzzy programming is the capability of explicitly measuring the degree of satisfaction of each objective function. This capability can assist the decision-maker to choose an efficient solution based on the degree of satisfaction of each objective function, and its relative importance (preference).

### 3.7.3.1 Auxiliary MILP Formulation

In the literature, there are different Auxiliary MILP formulation approaches which are discussed as follows:

- *Max–Min model:*

The max–min model was developed by Zimmermann (1978) and was the first fuzzy approach for solving an MOLP. However, it is well-known that max–min solutions may not be efficient or unique (Lai and Hwang, 1992, Li et al., 2006). Because of this, several augmented methods have been proposed.

$$\begin{aligned}
&\text{Maximise } \lambda \\
&s.t. \quad \mu_h(v) \geq \lambda, \qquad h = 1,\dots,4,\ v \in F(v) \\
&\qquad\ \lambda_0 \in [0,1]
\end{aligned} \tag{3.21}$$

- *Augmented max–min method:*

Lai and Hwang (1992) developed the following augmented max–min approach (referred to in this study as the LH method):

$$\begin{aligned}
&\text{Maximise } \lambda(v) = \lambda_0 + \delta \sum_h \theta_h \mu_h(v) \qquad h = 1,\dots,4,\ v \in F(v) \\
&s.t. \quad \lambda_h \leq \mu_h(v), \\
&\qquad\ \lambda_0 \in [0,1]
\end{aligned} \tag{3.22}$$

Where $\lambda_0$ represents the minimum degree of satisfaction with objectives. This is determined (along with variables $\mu_h(v)$) by solving the LH model in a single phase. $\delta$ is a very small positive number, usually set to be 0.01 efficient (Lai and Hwang, 1992).

*- Extended Werners (MW) method:*

Selim and Ozkarahan (2008) offered a modified version of Werners' approach (Werner and Knowles, 1988) as:

$$\begin{aligned}
&\text{Maximise } \lambda(v) = \gamma\lambda_0 + (1-\gamma)\sum_h \theta_h \lambda_h \\
&s.t. \quad \mu_h(v) \geq \lambda_0 + \lambda_h, \qquad\qquad h = 1,\ldots,4, v \in F(v), \gamma, \lambda_0 \\
&\qquad\; \lambda_h \in [0,1]
\end{aligned} \tag{3.23}$$

where $\lambda_0$ and $\mu_h(v)$ respectively represent the minimum degree of satisfaction of objectives and the degree of satisfaction of objective. These are simultaneously determined via solving the MW model. $\gamma$ is the coefficient of compensation and is set to 0.4 (Selim and Ozkarahan (2008)).

*- Two-phase method (LZL method)*

Li et al. (2006) proposed a two-phase fuzzy approach as below:

$$\begin{aligned}
&\text{Maximise } \lambda(v) = \sum_h \theta_h \mu_h(v) \\
&s.t. \quad \lambda_h^0 \leq \mu_h(v), \qquad\qquad h = 1,\ldots,4, v \in F(v) \\
&\qquad\; \lambda_h^0, \mu_h(v) \in [0,1]
\end{aligned} \tag{3.24}$$

where $\lambda_h^0$ denotes the minimum degree of satisfaction of the $h^{\text{th}}$ objective function. This is determined by solving Zimmermann's max–min approach (Zimmermann, 1978).

*- Torabi Hassini approach (TH method):*

Torabi and Hassini (2008) proposed their approach as:

$$
\begin{aligned}
&\text{Maximise } \lambda(v) = \gamma\lambda_0 + (1-\gamma)\sum_h \theta_h \mu_h(v) \\
&s.t. \quad \mu_h(v) \geq \lambda_0 + \lambda_h, , \qquad h = 1,\ldots,4, v \in F(v), \gamma, \lambda_0 \qquad (3.25) \\
&\qquad \gamma \in [0,1]
\end{aligned}
$$

where $\mu_h(v)$ and $\lambda_0 = \min_h\{\mu_h(v)\}$ respectively represent the degree of satisfaction of the $h$th objective function and the minimum degree of satisfaction of objectives. A new achievement function is defined in this formula as a convex combination of the lower bound for the degree of satisfaction with objectives $(\lambda_0)$, and the weighted sum of these degrees of achievement $(\mu_h(v))$, in order to ensure a balanced compromise solution. $\theta_h$ and $\gamma$ respectively indicate the relative importance of the $h$th objective function and the co-efficient of compensation. Decision-maker preferences determine the $\theta_h$ parameters, such that $\sum_h \theta_h = 1, \theta_h \geq 0$. $\gamma$ implicitly controls the objectives' minimum satisfaction levels as well as the degree of compromise among the objectives implicitly. Through adjusting the value of parameter $\gamma$, the proposed formula has the ability to yield both balanced and unbalanced compromised solutions for a given problem, based on the preferences of the decision-maker. A higher value for $\gamma$ indicates that more attention is given to obtaining a higher lower bound for the degree of satisfaction of objectives $(\lambda_0)$ (i.e. generating more balanced compromise solutions). Conversely, a lower value for $\gamma$ indicates that more attention is given to obtaining a solution with a high degree of satisfaction for objectives with higher levels of relative importance. No attention is given to the degree of satisfaction of other less important objectives. This generates unbalanced compromise solutions.

It is notable that a correlation exists between $\gamma$ and the range of $\theta_h$ values (i.e. $\max_h\{\theta_h\} - \min_h\{\theta_h\}$). In other words, a limited reasonable interval ( $\gamma$ ) could potentially be chosen for a specific $\theta$ vector. With relatively large values in this range, for example, the corresponding $\gamma$ value chosen should be small (e.g. smaller than 0.3), because of decision makers explicit preference for generating an unbalanced compromise solution. Using the TH method, the next section provides an interactive solution framework in order to solving the third model.

#### 3.7.3.2 Interactive fuzzy solution framework

The LH and MW single-phase methods directly solve the original model via just one auxiliary crisp model. However, the LH method sometimes generates inefficient solutions. Although the MW method usually yields an efficient solution, it is unbalanced and poorly compromised denoted by the fact the degrees of satisfaction of the objectives have considerable differences. These differences are often not acceptable to the decision-maker (Torabi and Hassini, 2008).

While the LZL is a two-phase approach that always produces an efficient solution, it requires more computational effort than single-phase approaches. This is especially the case when solving multi-objective mixed-integer linear problems.

Torabi and Hassini (2008) developed a new single-phase fuzzy method to remove the above deficiencies. Their proposed approach (referred to in this study as the TH method) is a hybrid of the MW and LH methods. A similar approach to that used by Li et al. (2006) can be used to demonstrate the efficiency of this TH method. Torabi and Hassini (2008) proposed the following interactive fuzzy solution process that can be utilised to solve the proposed possibility problem in this study:

***Step 1:*** Determine appropriate triangular possibility distributions for the imprecise parameters and formulate the original MOPMILP model for the CMDVRP-TW problem.

***Step 2:*** Convert the original fuzzy total cost of logistics $\widetilde{TC}$ into the three equivalent crisp objectives.

***Step 3:*** Given the minimum acceptable possibility level for imprecise parameters, $\beta$, convert the fuzzy constraints into the corresponding crisp ones, and formulate the auxiliary crisp MOMILP model.

***Step 4:*** Determine the positive ideal solution (PIS) and negative ideal solution (NIS) for each objective function by solving the corresponding MILP model;

***Step* 5:** Specify a linear membership function for each objective function.

***Step 6:*** Convert the auxiliary MOMILP model into an equivalent single-objective MILP using an auxiliary crisp formulation.

***Step 7:*** Given the coefficient of compensation $\gamma$ and relative importance of the fuzzy goals ( $\theta$ vector), solve the proposed auxiliary crisp model by the MIP solver. If the decision maker is satisfied with this current efficient compromise solution, stop. Otherwise, provide another efficient solution by changing the value of some controllable parameters say $\beta$ and $\gamma$ , and then go back to Step 3.

Figure 3.11 presents the implemented solution framework.

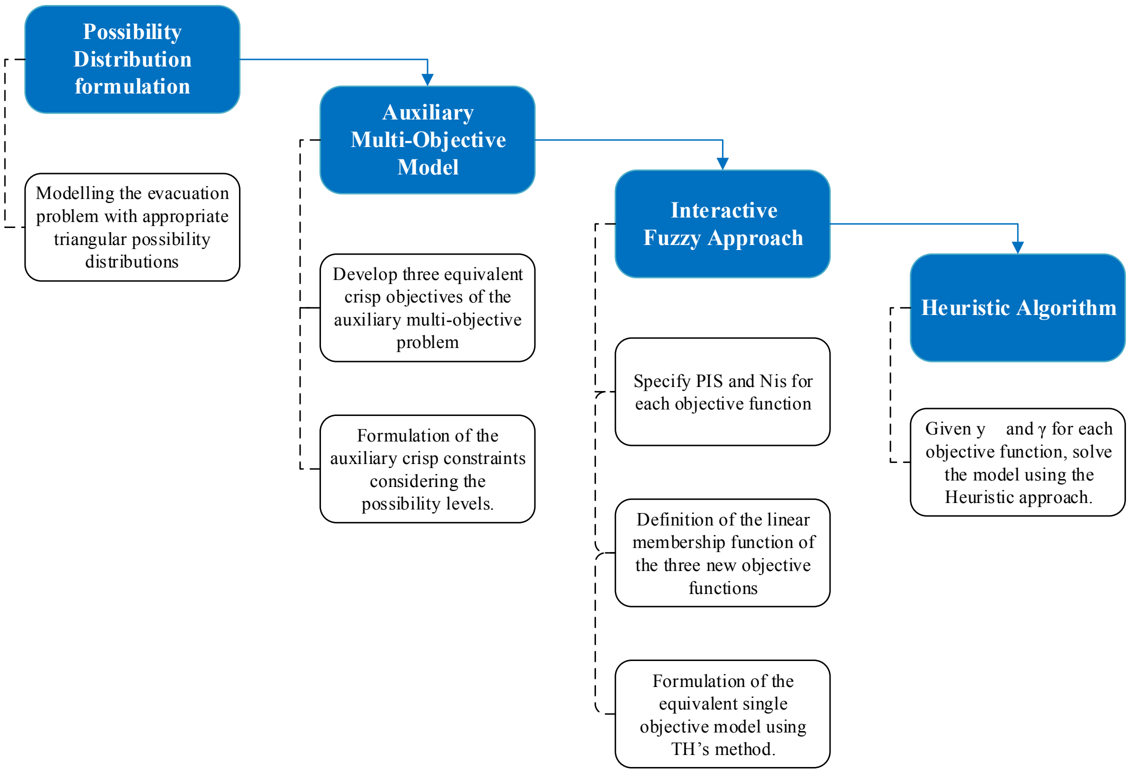



Figure 3.11 Solution framework of the possibilistic model

## 3.8 Summary

This chapter provided an extensive discussion of the research methodology employed in this study to formulate and solve the bushfire emergency evacuation problem. The chapter also described the study context and captured the key factors that drove the 2009 Black Saturday bushfires in Victoria. The chapter also explained how different required data are collated and processed. Data are collected from a wide range of interrelated sources including both infrastructure and emergency services organisations.

Several applicable approaches for formulation and solution were presented and the most appropriate and efficient approaches for the proposed problem were then discussed. Mixed-integer programming and vehicle routing problem modelling were found to be more suitable methods to formulate the problem in a deterministic manner for this study. However, the possibilistic programming was identified as a better approach to model short-notice evacuation under uncertainty. The efficient solution approaches for each formulation were explained. Epsilon constraint as Pareto-front optimal solution was shown as a suitable approach for the solving LEBMD-TW problem. Due to the complexity in the second and third models, a heuristic solution approach was also proposed. Furthermore, it was shown that the TH method could provide the most efficient results to be utilised as a solution approach for the third model.

The next chapter will describe the proposed formulations of the bushfire evacuation problem based on the approaches detailed in this chapter.

## Chapter 4

# Mathematical Formulations

## 4.1 Introduction

This chapter introduces three demand-based models that aim to generate bushfire evacuation plans by maximising total number of evacuees from assembly points via the most reliable routes within rigid time windows. The first model, Late Evacuation during Bushfire to Multiple Destinations with Time Windows (LEBMD-TW), is formulated as a mixed-integer programming approach. The second model, CMDVRP-TW, is formulated using a vehicle routing problem. Finally, the P-CMDVRP-TW integrates the concept of uncertainty in the parameters such as evacuation demand, time windows, travel times, and shelter capacity with the vehicle routing problem detailed. Each formulation is accompanied by a list of assumptions in each section, made in order to realistically model the problem aiming to maximise of number of evacuated people from affected areas.

## 4.2 Model I (LEBMD-TW): Multi-objective modelling

The first model is formulated as a mixed-integer multi objective optimisation problem to improve the efficiency of late evacuation responses by challenging multi-objective programming with aggregated objective functions of the maximum evacuation of people in need and minimum utilisation of resources among the safest routes. Two bushfire-wide aggregated objective functions addressed the overall transferred evacuees via less risk.

### 4.2.1 Modelling assumptions in LEBMD-TW

The modelling is based on the following key assumptions:

- Shelters are pre-designated by the fire agency - Country Fire Authority (CFA).
- The number and capacity of shelters and rescue vehicles are finite.
- The late evacuee population in each assembly point is known.
- Access to some routes and shelters is restricted by bushfire propagation.
- The availability of assembly points and routes is subject to rigid time windows.
- There is no background traffic outside the affected region.

### 4.2.2 Sets and indices

*Sets*

$I$ set of evacuation points (origins)

$J$ set of candidate shelters (destinations)

$V$ set of vehicle types

$K$ set of routes across evacuation points $i$ and shelters $j$

$L$ set of route sections

*Indices*

$i$ index of evacuation points, $(i \in I)$

$j$ index of candidate shelter, $(j \in J)$

$v$ index of vehicle types, $(v \in V)$

$l$ index of road sections, $(l \subset L)$

$k$ index of route $k$ among evacuation points and shelters, $(k \in K)$

### 4.2.3 Parameters

$\varphi^v$ route's occupied capacity by one unit of vehicle type $v$ $(v \in V)$.

$\theta^v$ usage cost of vehicle type $v$ $(v \in V)$.

$\lambda_{ijk}^v$ capacity of route $k$ along evacuation point $i$ to shelter $j$ for vehicle $v$ $(i \in I; j \in J; k \in K)$.

$C_j$ capacity of assigned shelter $j$ $(j \in J)$.

$P_i$ population of late evacuees at assembly point of township $i$ $(i \in I)$.

$\tau_{ijk}$ traversal time of route $k$ between assembly point $i$ to shelter $j$ $(i \in I; j \in J; k \in K)$.

$T$ time impedance parameter due to road congestions.

$DT$ dwell time (vehicle preparation, boarding/alighting of evacuees).

$\overline{\mu}_{ijk}$ disruption risk of route $k$ between node $i$ and $j$ $(i \in I; j \in J; k \in K)$.

$\Omega$ number of candidate shelters.

$w$ weighted sum coefficient.

$TV_v$ number of available vehicles type $v$ $(v \in V)$.

$VC_v$ vehicle capacity of type $v$ $(v \in V)$.

$TW_i$ availability time window of evacuation point $i$ $(i \in I)$.

$TWR_{ijk}$ availability time window of *k* route $(i \in I; j \in J; k \in K)$.

$\alpha_j$ facilities functioning vector; 1, if shelter *j* is available; 0, otherwise. $(j \in J)$.

$\beta_{ijk}$ link/route disruption matrix; 1 if route *k* is accessible between point *i* and shelter *j*; 0, otherwise; $(i \in I; j \in J; k \in K)$.

### 4.2.4 Decision variables

Two sets of decision variables are used to represent the maximal short-notice evacuation coverage problem and the equivalent minimal resource location-allocation during an emergency situation. The variables are:

- $X_{ijk}$ Number of transferred late evacuees from assembly point *i* to functioning shelter *j* throughout *k* route.
- $NV_{ijk}^{v}$ Quantity of vehicle type *v* in need to be routed to transfer evacuees via route *k* from the assembly point *i* to functioning shelter *j*.
- $\gamma_j$ If evacuees are transferred to the dedicated shelter *j*; 0, otherwise;
- $\sigma_j$ If a shelter is assigned to candidate place *j*; 0, otherwise;

Variable $\gamma_j$ ensures that late evacuees from any assembly point can be transported to the designated shelters until they are operational. Accordingly, the decision variable $\sigma_j$, measures if shelter *j* is chosen as a safe shelter to transfer evacuees or not.

Two auxiliary integer decision variables are also applied to improve the results:

$M_{ijk}$ Number of times that vehicle *v* travels between assembly point *i* to candidate shelter *j* via route *k*

$X'_{ijk}$ Unoccupied seats in the last trip of assigned vehicle.

### 4.2.5 Objective function

The following LEBMD-TW model objectives are:

- To maximise the number of evacuated people using the most reliable routes (minimum cumulative disruption risk) to the nearest functioning shelters within the rigid clearance times (equation 4.1); and
- To minimise the allocation of functioning resources (the number of functioning shelters and rescue vehicles) (equation 4.2).

$$f_1 = \sum_i \sum_j \sum_k X_{ijk} \left(1 - \bar{\mu}_{ijk}\right) \tag{4.1}$$

$$f_2 = w_1 \sum_i \sum_j \sum_k \sum_v \theta^v NV_{ijk}^v + w_2 \sum_j \sigma_j \tag{4.2}$$

The first objective function (equation 4.1) maximises the number of evacuees at assembly point *i* who must then be transferred to shelter *j* in the minimum time possible via the safest route.

The second objective function (equation 4.2) minimises the total number of designated shelters and rescue vehicles. The goal is to decrease the cost of allocating new facilities and utilising the minimum number of shelters and rescue vehicles needed for evacuees. $w_1$ and $w_2$ are utilised as auxiliary coefficients in the weighted sum method, and are selected in the range of [0-1], summing to one to represent the weight of impression for each parameter.

### 4.2.6 Constraints

The above objective functions are subject to the following constraints. Inequalities (equation 4.3) and (equation 4.4) are embedded in the model as the maximum number of shelters covering location-allocation constraints. Hence, constraint (equation 4.3) restricts the number of allocated shelters to the maximum number available.

$$\sum_j \sigma_j \leq \Omega \tag{4.3}$$

Constraint (equation 4.4) guarantees that the candidate shelter must first be both functioning and available in order to be allocated.

$$\gamma_j \leq \alpha_j \sigma_j \qquad \forall j \in J \tag{4.4}$$

Constraint (equation 4.5) is a shelter capacity expansion constraint and ensures that people at affected point *i* will only be evacuated and transferred to shelter *j* if shelter *j* is accessible and available. In addition, since each capacitated shelter is expected to serve the maximum number of late evacuees, it is assumed that each rescue vehicle will always travel directly between its assembly point and the designated shelter, rather than travelling to additional places for further evacuee boarding. This constraint, therefore, ensures that the number of evacuees transferred to the designated shelter *j* will not exceed shelter's capacity.

$$\sum_i \sum_k X_{ijk} \le C_j \gamma_j \qquad \forall j \in J \tag{4.5}$$

Constraint (4.6) ensures that evacuees at assembly point *i* will only evacuate and transfer to shelter *j* if there is an accessible and available road connection between the origin and destination.

$$X_{ijk} \le \beta_{ijk} P_i \qquad \forall i \in I, j \in J, k \in K, v \in V \tag{4.6}$$

Constraint (4.7) links transferred evacuees and assigned vehicles. This constraint mandates that the maximum evacuation time for a round trip of each vehicle from assembly point *i* ( $2 \times \tau_{ijk}$ ) must not exceed the available clearance time. The evacuation time for each trip has two components. The clearance time will be chosen based on minimum values of these two critical components - the route and the township availability. This constraint also ensures that each vehicle cannot carry more late evacuees than its seating capacity.

$$M_{ijk} \times \left(\left(2 \times \tau_{ijk}(1+T)\right) + DT\right) \le Minimum\left(TW_i, TWR_{ijk}\right) \quad \forall i \in I, j \in J, k \in K \tag{4.7}$$

In constraint (4.8), $X'_{ijk}$ is a dummy variable defined to compute the number of unoccupied seats in the last trip of assigned vehice\s. Equation (4.8) therefore mandates that number of required trips to transfer evacuees ( $M_{ijk}$ ) is an integer.

$$X_{ijk} + X'_{ijk} = M_{ijk} \sum_{v} VC_v NV_{ijk}^{v} \qquad \forall i \in I, j \in J, k \in K \qquad (4.8)$$

Constraint (4.9) ensures that unoccupied seats in the last trip are less than the total capacity of assigned vehicle\s.

$$X'_{ijk} < \sum_{v} VC_v NV_{ijk}^{v} \qquad \forall i \in I, j \in J, k \in K \qquad (4.9)$$

Upon realisation of infrastructure disruptions, the population of the area in each of evacuee assembly points is determined. A number of late evacuees is then allocated to the designated shelters *j*, denoted as $\gamma_j$. Constraint (4.10) therefore ensures that the number of late evacuees to be transported from an assembly point *i* to shelter *j* does not exceed the population of the area that each assembly point represents.

$$\sum_{i} \sum_{k} X_{ijk} \le P_i \qquad \forall i \in I \qquad (4.10)$$

Constraint (4.11) mandates that the total number of assigned rescue vehicles is $TV_v$ (the total number of available vehicles for the entire evacuation process).

$$\sum_{i} \sum_{j} \sum_{k} NV_{ijk}^{v} \le TV_v \qquad \forall v \in V \qquad (4.11)$$

Constraint (4.12) is the route passage capability constraint, and limits the maximum number of assigned vehicles to each route based on the capacity of that route.

$$\sum_{v} \varphi^{v} NV_{ijk}^{v} \le \lambda_{ijk}^{v} \qquad \forall i \in I, j \in J, k \in K \qquad (4.12)$$

Constraints (4.13) and (4.14) are non-negativity and integerality constraints. Constraint (4.13) expresses that negative numbers could not feasibly be considered as variables. Constraint (4.14) restricts the assignment of shelters and transferring issues to binary values, as $\sigma_j, \gamma_j$ are either allocated or they are not.

$$X_{ijk}, X'_{ijk}, M_{ijk}, NV_{ijk}^{v} \in Z^{+} \quad \text{Integer} \qquad \forall i \in I, j \in J, k \in K, v \in V \qquad (4.13)$$

$$\sigma_j, \gamma_j \in \{0,1\} \qquad \forall j \in J \qquad (4.14)$$

## 4.3 Model II (CMDVRP-TW): Deterministic vehicle routing problem modelling

The second model is a capacitated multi-destination vehicle routing problem with time windows (CMDVRP-TW) developed for this research and has the following characteristics:

### 4.3.1 Modelling assumptions

- The population and time window for servicing each assembly point is known.
- The number and locations of the capacitated shelters are known.
- Each route, assembly point and shelter can be served by several vehicles.
- Vehicles have limited boarding capacity.

### 4.3.2 Sets and indices

Considering the above assumptions, the proposed Capacitated Multiple Destination Vehicle Routing Problem with Time Window (CMDVRP-TW) model is formulated as below:

$I$ set of assembly points $I \in \{1,2,\ldots,|I|\}$

$J$ set of all shelters $J \in \{|I|+1,|I|+2,\ldots,|I|+|J|\}$

$S^m$ set of the available transportation network at time window *m*, $m \in \{1,2,\ldots,|I|\}$

$S^m_{.i}$ set of all the arrival routes to node *i* at time period *m*, $i \in (I \cup J)$

$S^m_{i.}$ set of all the egress routes from node *i* at time period *m*, $i \in (I \cup J)$

*Indices*

$i$ index for assembly points

$j, j'$ index for shelters

$m$ index for time periods ($m \in \{1,2,\ldots,|I|\}$, e.g. $m=3$ indicates time period between $T_2$ and $T_3$)

$k$ index for time windows ($k \in I$, e.g., $k=3$ is the time from 0 to $T_3$)

$n$ index for $n^{th}$ vehicle

$r$ index of routes

### 4.3.3 Decision variables

The following decision variables are defined to create the configuration of the emergency evacuation:

$X_{ijr}^{nm}$ Number of times that the vehicle travels from node *i* to node *j* in time window *m* by *n*th vehicle ($i \in (I \cup J)$).

*Binary variables*

$\alpha_i^{nm}$ Evacuation process starts node ($i \in I$) at time window *m*.

$\beta_i^{nm}$ Evacuation process finish node at time window *m*, ($i \in (I \cup J)$).

$Z_{ij}^{nm}$ 1 if bus n in time period m from town *i* to shelter *j* is assigned, 0 otherwise.

$Y_j$ 1 if shelter *j* is assigned,0 otherwise.

$P_{ijj'}^{nm}$ Auxiliary variable for sub tour elimination.

### 4.3.4 Parameters

$D_i$ number of evacuees in assembly point $i$, $(i \in I)$.

$V$ maximum boarding capacity of the rescue vehicle.

$C_j$ maximum available capacity of $j^{th}$ shelter $(j \in J)$.

$T_k$ available evacuation time window (clearance time) for each assembly point ($k \in I$, e.g. assembly point *i* is available from 0 to $T_{k=i}$).

$t_{ijr}$ travel time between assembly point *i* and shelter *j* via route *r*.

$B$ big number.

### 4.3.5 Objective function

The objective function of the model to be maximised is given by (equation 4.15). This objective function maximises total number of transferred evacuees from the assembly points to safer places via safest routes:

$$\text{Maximise} \sum_{m\in I}\sum_{i\in I}\sum_{(j)\in S_{i.}^{m}} X_{ij}^{nm} V(1-\mu_{ij}) \tag{4.15}$$

## 4.3.6 Constraints

The objective function then is subject to a number of constraints. Constraint (4.16) expresses the absorption capacity of each shelter. Put differently, the constraint mandates that sum of the transferred evacuees from various towns to shelter $j^{th}$ in all the time periods, and this should be less than the total capacity of shelter $j^{\mathrm{th}}$ plus vehicle capacity. The capacity of the vehicle is added to the right hand side of constraint to avoid left over of population when it is less than vehicles capacity.

$$\sum_{m=1}^{k}\sum_{n=1}^{N}\sum_{(i,r)\in S_{.j}^{m}} X_{ijr}^{nm} V \langle C_j + V \qquad \forall j \in J, \forall k \in I \tag{4.16}$$

Constraint (4.17) restricts the total vehicles boarding capacity to the population of evacuees in each town. In other words, this constraint measures that the number of evacuees evacuated from town *i* to all shelters in all time period should be less equal than the entire population of town *i*. In the same way to the previous constraint, vehicle capacity is added to right side of the equation to prevent left over population in the last service of vehicle.

$$\sum_{m=1}^{k}\sum_{n=1}^{N}\sum_{(j,r)\in S_{i.}^{m}} X_{ijr}^{nm} V \langle D_i + V \qquad \forall i \in I, \forall k \in I \tag{4.17}$$

Constraint (4.18) imposes a constraint that all vehicles start from a township in each time period.

$$\sum_{i\in I} \alpha_i^{nm} = 1 \qquad \forall m \in I, n \in N \tag{4.18}$$

Constraint (4.19) restricts the starting of vehicles such that vehicles cannot start their services from shelters in the first time window.

$$\sum_{j \in J} \alpha_j^{nm} = 0 \qquad \forall m \in \{1\}, n \in N \qquad (4.19)$$

Constraint (4.20) defines the finish point of vehicles at each time window while constraint (4.21) indicates that vehicle services finish only at designated shelters at the end of the last time window.

$$\sum_{i \in (I \cup J)} \beta_i^{nm} = 1 \qquad \forall m \in I, n \in N \qquad (4.20)$$

$$\sum_{i \in I} \beta_i^{nm} = 0 \qquad \forall m \in \{|I|\}, n \in N \qquad (4.21)$$

Constraint (4.22) guarantees the continued flow of each vehicle to start its next service from its last finishing point.

$$\beta_{i \in (I \cup J)}^{nm} = \alpha_{i \in I}^{n,m+1} \qquad \forall m \in \{1, \ldots, |I| - 1\}, n \in N \qquad (4.22)$$

Constraint (4.23) ensures flow conservation of the network within each time window. For each vehicle, the quantity that arrives in a node must be equal to the quantity that departs.

$$\beta_{i \in (I \cup J)}^{nm} + \sum_{(j,r) \in S_{.i}^m} X_{ijr}^{nm} = \alpha_{i \in I}^{nm} + \sum_{(i,r) \in S_{i.}^m} X_{ijr}^{mn} \qquad \forall i \in (I \cup J), m \in I, n \in N \qquad (4.23)$$

Constraint (4.24) is a time window constraint and guarantees that the total time travelled by vehicles does not exceed the total available time windows for each township.

$$\sum_{m=1}^{k} \sum_{(i,j,r) \in S^m} X_{ijr}^{nm} t_{ijr} + \sum_{m=1}^{k} \sum_{(i,j,r) \in S^m} X_{jir}^{nm} t_{jir} \le T_k \qquad \forall m \in I, n \in N \qquad (4.24)$$

Constraint (4.25-4.31) are VRP sub-tour elimination constraints.

$$\sum_{r\in S^m} X_{ijr}^{nm} + \sum_{r\in S^m} X_{jir}^{nm} \le Z_{ij}^{nm} B \qquad \forall i \in I, J \in J, m \in I, n \in N \qquad (4.25)$$

$$\sum_{r\in S^m} X_{ijr}^{nm} + \sum_{r\in S^m} X_{jir}^{nm} \ge Z_{ij}^{nm} \qquad \forall i \in I, J \in J, m \in I, n \in N \qquad (4.26)$$

$$Z_{ij}^{nm} \le Y_j \qquad \forall i \in I, J \in J, m \in I, n \in N \qquad (4.27)$$

$$Z_{ij}^{nm} + Z_{ji}^{nm} \ge 2 \times P_{ijj'}^{nm} \qquad \forall m \in I, i \in I, n \in N, (j, j' \in J, \forall j \ne j') \qquad (4.28)$$

$$\sum_{i\in I} P_{ijj'}^{nm} \le 1 \qquad \forall m \in I, n \in N, (j, j' \in J, \forall j \ne j') \qquad (4.29)$$

$$\sum_{i\in I} \sum_{j\in J} \sum_{j'\ne j} P_{ijj'}^{nm} \ge \sum_{j} Y_j - 1 \qquad \forall m \in I, n \in N \qquad (4.30)$$

$$\sum_{j\in J} Z_{ij}^{nm} \ge \alpha_i^{nm} \qquad \forall i \in I, n \in N, m \in I \qquad (4.31)$$

Constraint (4.32) must be an integer.

$$X_{ijr}^{nm} \text{ is integer} \qquad \forall (i.j,r) \in S^m, \forall m \in I \qquad (4.32)$$

Constraints (4.33-4.36) determine the domain for the binary variables.

$$\alpha_i^{nm} \in \{0,1\} \qquad \forall i \in I, m \in I, n \in N \qquad (4.33)$$

$$\beta_i^{nm} \in \{0,1\} \qquad \forall i \in (I \cup J), m \in I, n \in N \qquad (4.34)$$

$$Z_{ij}^{nm} \in \{0,1\} \qquad \forall i \in (I \cup J), j \in J, n \in N, m \in I \qquad (4.35)$$

$$P_{ijj'}^{nm} \in \{0,1\} \qquad \forall i \in (I \cup J), (j, j' \in J, \forall j \ne j'), n \in N, m \in I \qquad (4.36)$$

## 4.4 Model III (P-CMDVRP-TW): Possibilistic Vehicle Routing Problem modelling

### 4.4.1 Modelling assumptions

A capacitated multi-destination vehicle routing problem with time windows (CMDVRP-TW) is integral to this research to cover the uncertainty related to bushfire evacuation. The model has the following characteristics:

- Evacuee population, clearance times, travel times, shelter capacities, and evacuee population are fuzzy variables.
- Vehicles used have limited boarding capacity.
- The number and locations of shelters is known.
- Each assembly point, route and shelter is able to be served by several rescue vehicles.

### 4.4.2 Sets and indices

Sets and indices are:

*Sets*

$I$ set of assembly points $I \in \{1,2,\ldots,|I|\}$

$J$ set of all shelters $J \in \{|I|+1,|I|+2,\ldots,|I|+|J|\}$

$R$ Set of routes

$S^m$ set of the available transportation network at time window *m*, $m \in \{1,2,\ldots,|I|\}$

$S^m_{.i}$ set of all the arrival routes to node *i* at time period *m*, $i \in (I \cup J)$

$S^m_{i.}$ set of all the egress routes from node *i* at time period *m*, $i \in (I \cup J)$

*Indices*

$i$ index for assembly points

$j$ index for shelters

$m$ index for time periods ($m \in \{1,2, \ldots,|I|\}$, e.g. $m = 3$ indicates time period between $T_2$ and $T_3$)

$k$ index for time windows ( $k \in I$, e.g., $k = 2$ is the time from 0 to $T_3$)

$n$ index for $n^{th}$ vehicle

$r$ index of routes

### 4.4.3 Parameters

$\widetilde{D}_i$ number of evacuees in assembly point $i$, $(i \in I)$.

$V$ maximum boarding capacity of the rescue vehicle.

$\widetilde{C}_j$ fuzzy capacity of $j^{th}$ shelter $(j \in J)$.

$\widetilde{T}_k$ available fuzzy evacuation time window (clearance time) for each assembly point ($k \in I$, e.g. assembly point $i$ is available from 0 to $T_{k=i}$).

$\widetilde{t}_{ijr}$ fuzzy travel time between assembly point $i$ and shelter $j$ via route $r$.

$\widetilde{\mu}_{ijr}$ fuzzy disruption risk of route $r$ between assembly point $i$ and shelter $j$.

### 4.4.4 Decision variables

The following decision variables are defined to create the configuration of the emergency evacuation:

$X_{ijr}^{nm}$ Number of times that the vehicle travels from node $i$ to node $j$ at time window $m$ by $n^{\text{th}}$ vehicle ($i \in (I \cup J)$).

*Binary variables*

$\alpha_i^{nm}$ Evacuation process starts node ($i \in I$) at time window *m*.

$\beta_i^{nm}$ Evacuation process finish node at time window *m*, ($i \in (I \cup J)$).

$Z_{ij}^{nm}$ 1 if bus *n* in time period m from town *i* to shelter *j* is assigned, 0 otherwise.

$Y_j$ 1 if shelter *j* is assigned,0 otherwise.

$P_{ijj'}^{nm}$ Auxiliary variable for sub tour elimination.

### 4.4.5 Objective function

The fuzzy objective and constraints functions are usually subjectively determined by the decision-maker and preference-based in flexible programming models. For each imprecise parameter, possibilistic programming is based on determining the objective possibility of the event occurring (Torabi and Hassini, 2008, Buckley, 1988). The related possibility distributions are calculated objectively based on available historical data that is comparable to the probability distributions. The proposed fuzzy programming model is in this category due to the ambiguity of some parameters in the total cost objective function, of some technological coefficients; and some of the constraints. The proposed multi-destination capacitated vehicle routing problem with time window (CMDVRP-TW) model is formulated as below:

$$\widetilde{f}_{Max} = \sum_{m\in I}\sum_{i\in I}\sum_{(j,r)\in S_{i.}^{m}} X_{ijr}^{mn} V(1-\widetilde{\mu}_{ijr}) \tag{4.37}$$

This objective function (equation 4.37) aims to maximise total number of transferred evacuees from the assembly points to shelters via the most reliable routes $(1-\widetilde{\mu}_{ijr})$.

### 4.4.6 Constraints

The objective function then is subject to the following constraints:
Constraint (4.38) is shelter absorption capacity.

$$\sum_{m=1}^{k}\sum_{(i,r)\in S_{.j}^{m}} X_{ijr}^{mn} V < \widetilde{C}_j + V \qquad \forall j\in J, \forall k\in I \tag{4.38}$$

Constraint (4.39) is the rescue vehicle passenger capacity.

$$\sum_{m=1}^{k}\sum_{(i,r)\in S_{i.}^{m}} X_{ijr}^{mn} V < \widetilde{D}_i + V \qquad \forall i\in I, \forall k\in I \tag{4.39}$$

Constraint (4.40) requires all vehicles to start from the assembly points in each time window.

$$\sum_{i\in I}\alpha_i^{nm} = 1 \qquad \forall m\in I, n\in N \tag{4.40}$$

Constraints (4.41-4.42) restrict the start and finish point of each vehicle at each time window. Rescue vehicles may start in any town, and they can proceed from a shelter to their next assembly point in the next time window (m>1). Vehicles may finish service in either a shelter or an assembly point in each time window except for the last service where they should finish in one of the assigned shelters (m=[I]).

$$\sum_{i\in(I\cup J)}\beta_i^{nm} = 1 \qquad \forall m\in I, n\in N \qquad (4.41)$$

$$\sum_{i\in I}\beta_i^{nm} = 0 \qquad \forall m\in\{|I|\}, n\in N \qquad (4.42)$$

Constraint (4.43) guarantees a continuous flow with vehicles starting their next service from their previous finishing point.

$$\beta_{i\in(I\cup J)}^{nm} = \alpha_{i\in I}^{n,m+1} \qquad \forall m\in\{1,\ldots,|I|-1\}, n\in N \qquad (4.43)$$

Constraint (4.44) ensures flow conservation of the network within each time window. The quantity of vehicles that arrive at a node must equal the quantity that departs.

$$\beta_{i\in(I\cup J)}^{nm} + \sum_{(j,r)\in S_{.i}^{m}} X_{ijr}^{nm} = \alpha_{i\in I}^{nm} + \sum_{(i,r)\in S_{i.}^{m}} X_{ijr}^{mn} \qquad \forall i\in(I\cup J), m\in I, n\in N \qquad (4.44)$$

Constraint (4.45) is a time window and guarantees that total vehicle travel time does not exceed the total available evacuation time window.

$$\sum_{m=1}^{k}\sum_{(i,j,r)\in S^m} X_{ijr}^{mn}\tilde{t}_{ijr} + \sum_{m=1}^{k}\sum_{(i,j,r)\in S^m} X_{jir}^{mn}\tilde{t}_{jir} \le \tilde{T}_k \qquad \forall m\in I, n\in N \qquad (4.45)$$

Constraints (4.46-4.52) are sub-tour elimination constraints.

$$\sum_{r\in S^m} X_{ijr}^{nm} + \sum_{r\in S^m} X_{jir}^{nm} \le Z_{ij}^{nm}B \qquad \forall i\in I, J\in J, m\in I, n\in N \qquad (4.46)$$

$$\sum_{r\in S^m} X_{ijr}^{nm} + \sum_{r\in S^m} X_{jir}^{nm} \ge Z_{ij}^{nm} \qquad \forall i\in I, J\in J, m\in I, n\in N \qquad (4.47)$$

$$Z_{ij}^{nm} \le Y_j \qquad \forall i\in I, J\in J, m\in I, n\in N \qquad (4.48)$$

$$Z_{ij}^{nm} + Z_{ji}^{nm} \ge 2\times P_{ijj'}^{nm} \qquad \forall m\in I, i\in I, n\in N, (j, j'\in J, \forall j\ne j') \qquad (4.49)$$

$$\sum_{i\in I} P_{ijj'}^{nm} \le 1 \qquad \forall m\in I, n\in N, (j, j'\in J, \forall j\ne j') \qquad (4.50)$$

$$\sum_{i \in I} \sum_{j \in J} \sum_{j' \neq j} P_{ijj'}^{nm} \geq \sum_{j} Y_j - 1 \qquad \forall m \in I, n \in N \tag{4.51}$$

$$\sum_{j \in J} Z_{ij}^{nm} \geq \alpha_i^{nm} \qquad \forall i \in I, n \in N, m \in I \tag{4.52}$$

Constraints (4.53-4.57) define the domain of variables.

$$X_{ijr}^{nm} \text{ is integer} \qquad \forall (i.j,r) \in S^m, \forall m \in I \tag{4.53}$$

$$\alpha_i^{nm} \in \{0,1\} \qquad \forall i \in I, m \in I, n \in N \tag{4.54}$$

$$\beta_i^{nm} \in \{0,1\} \qquad \forall i \in (I \cup J), m \in I, n \in N \tag{4.55}$$

$$Z_{ij}^{nm} \in \{0,1\} \qquad \forall i \in (I \cup J), j \in J, n \in N, m \in I \tag{4.56}$$

$$P_{ijj'}^{nm} \in \{0,1\} \qquad \forall i \in (I \cup J), (j, j' \in J, \forall j \neq j'), n \in N, m \in I \tag{4.57}$$

### 4.4.7 Auxiliary multi-objective mixed-integer model

#### *Fuzzification and defuzzification*

The crisp variable must be fuzzified into a *fuzzy* variable due to its linguistic characteristic (Sakawa, 2013). After the calculations, the *fuzzy* result should be defuzzified back to the crisp result as the final result. This is necessary for the time-based variables in the problem, such as the transportation time and time window (clearance time).

Due to the unavailability of necessary data, critical parameters such as evacuee demands and shelter capacity levels are assumed to be imprecise (and therefore fuzzy). In addition, each fuzzy parameter will be represented by the pattern of the triangular fuzzy number. Due to computational efficiency and the simplicity of data acquisition, the triangular possibility distribution is the most common tool for modelling ambiguous parameters (Zimmermann, 1978).

Generally, a possibility distribution can be defined as the degree of occurrence of an event with imprecise data (Zadeh, 1999). As Figure 4.1 indicates, the triangular possibility distribution of fuzzy number $\tilde{t}$ with possibility level of $\Omega$ is calculated as:

$t_{\Omega} = [(t^m - t^p).\Omega + t^p, t^o - (t^o - t^m).\Omega]$.

In the fuzzy number equation: $\tilde{t} = (t^p, t^m, t^o), n^p$, $n^m$ and $n^o$ are respectively the most pessimistic value, the most possible value, and the most optimistic value of $\tilde{n}$ , as estimated by the decision-maker.

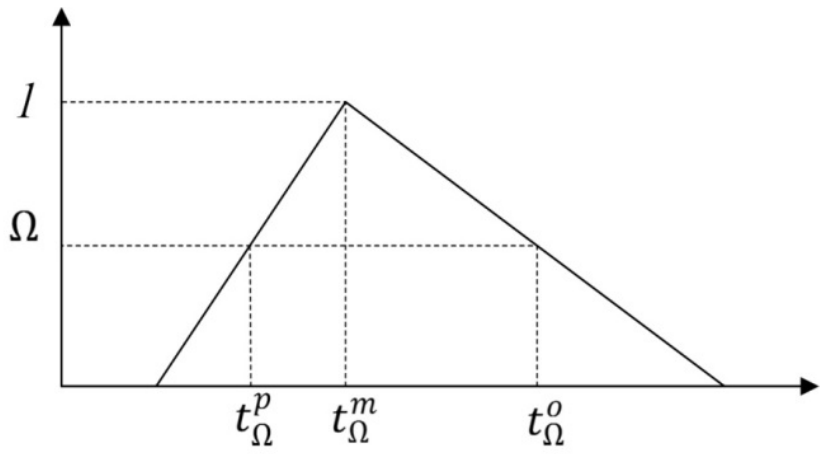



Figure 4.1 The triangular possibility distribution of $\tilde{\boldsymbol{t}}$ with possibility level of $\boldsymbol{\Omega}$

The objective function is transformed into a fuzzy one by the presence of imprecise coefficients. These can be fully defined by three prominent points ($Z^p$, 0), ($Z^m$, 1) and ($Z^o$, 0). By pushing these three prominent points towards the right, the imprecise objective can be maximised. That is, the objective maximisation is achieved by the simultaneous maximisation of $Z^p$, $Z^m$ and $Z^o$. To determine the compromise solution, Lai and Hwang's approach is adopted (Lai and Hwang, 1992). The maximisation of $Z^p$, $Z^m$ and $Z^o$ is replaced by the maximising of the highest possible value of the imprecise objective function ($Z^m$), minimising the risk of obtaining lower pessimistic objective values (i.e., transporting the lowest number of evacuees via less reliable routes,($Z^m$-$Z^p$) and maximising the possibility of obtaining higher optimistic values (i.e., transporting the highest number of evacuees via the most reliable routes, ($Z^o - Z^m$). As Figure 4.2 indicates, the three replaced objective functions guarantee that the possibility distribution is pushed toward the right.

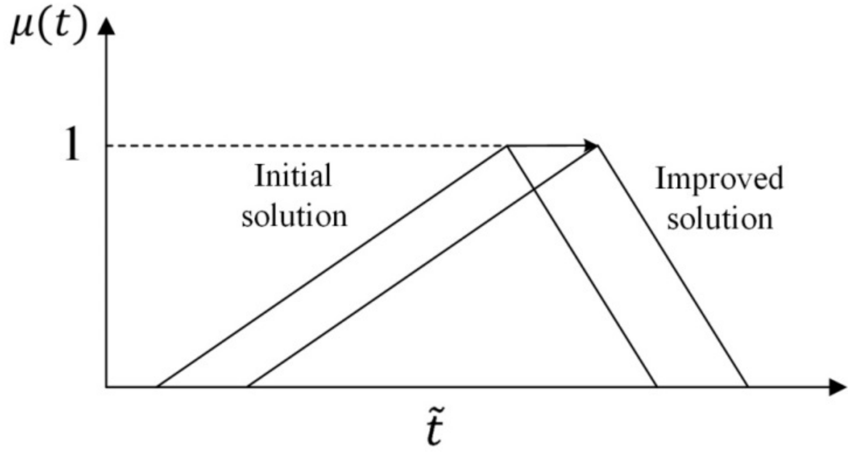



Figure 4.2 The strategy to maximise the total objective function

The original fuzzy objective (equation 4.37) is therefore replaced by the following three crisp objectives in order to obtain the compromise solution:

$$Max\ f_1 = f^m = \sum_{m\in I}\sum_{i\in I}\sum_{(j,r)\in S_{i.}^m} X_{ijr}^{mn} V (1-\mu^m{}_{ijr}) \tag{4.58}$$

$$Min\ f_2 = f^m - f^p = \sum_{m\in I}\sum_{i\in I}\sum_{(j,r)\in S_{i.}^m} X_{ijr}^{mn} V (1-(\mu^m{}_{ijr} - \mu^p{}_{ijr})) \tag{4.59}$$

$$Max\ f_3 = f^o - f^m = \sum_{m\in I}\sum_{i\in I}\sum_{(j,r)\in S_{i.}^m} X_{ijr}^{mn} V (1-(\mu^o{}_{ijr} - \mu^m{}_{ijr})) \tag{4.60}$$

The weighted average approach is implemented to convert the parameters $\widetilde{T}_k$, $\widetilde{D}_j$ $\widetilde{C}_j$ and $\widetilde{t}_{ijr}$ into crisp numbers in order to deal with the uncertainties in evacuee population, travel times, time windows (clearance times) and shelter capacities in the Possibilistic model's constraints. If the minimum acceptable possibility, $\eta$, is given, the corresponding auxiliary crisp inequality constraints can be represented as follows:

*subject to:*

$$\sum_{m=1}^{k}\sum_{(i,r)\in S_{.j}^m} X_{ijr}^{mn} V < (w_1'.C_{j,\eta}^p + w_2'.C_{j,\eta}^m + w_3'.C_{j,\eta}^o) + V \qquad \forall j\in J, \forall k\in I \tag{4.61}$$

$$\sum_{m=1}^{k}\sum_{(i,r)\in S_{i.}^m} X_{ijr}^{mn} V < (w_1''.D_{j,\eta}^p + w_2''.D_{j,\eta}^m + w_3''.D_{j,\eta}^o) + V \qquad \forall j\in J, \forall k\in I \tag{4.62}$$

$$\sum_{m=1}^{k} \sum_{(i,j,r)\in S^m} X_{ijr}^{mn} (w_1'''.t_{ijr,\eta}^{p} + w_2'''.t_{ijr,\eta}^{m} + w_3'''.t_{ijr,\eta}^{o})$$
$$+ \sum_{m=1}^{k} \sum_{(i,j,r)\in S^m} X_{jir}^{mn} (w_1'''.t_{jir,\eta}^{p} + w_2'''.t_{jir,\eta}^{m} + w_3'''.t_{jir,\eta}^{o}) \qquad \forall k \in I \qquad (4.63)$$
$$\leq (w_1.T_{k,\eta}^{p} + w_2.T_{k,\eta}^{m} + w_3.T_{k,\eta}^{o})$$

where $w_1$, $w_2$ and $w_3$ respectively denote the weight of the most pessimistic, most possible and most optimistic value of the imprecise parameters, and $\sum_{i=1}^{3} w_i = 1, i \in \{1,2,3\}$. The same can be said for $w'$, $w''$, and $w'''$. The weights can be determined subjectively by the decision-maker's knowledge and experience. Based on the suggestion of Lai and Hwang (1992), $\eta$ is set to 1/6, 4/6, 1/6 and 1/2 respectively.

## 4.5 Summary

In this chapter, three emergency evacuation formulations were developed addressing routing and scheduling of the rescue fleet in a practical manner for short-notice bushfire evacuation. Three mathematical models were derived:

I) Late Evacuation during Bushfire to Multiple Destinations with Time Windows (LEBMD-TW problem),

II) II) Capacitated Multiple Destination Vehicle Routing Problem with Time Window (CMDVRP-TW), and

III) III) Possibilistic Capacitated Multiple Destination Vehicle Routing Problem with Time Window (P-CMDVRP-TW) model.

The objective functions of the models are defined as maximisation of the total evacuated people via most reliable routes and minimum resources, which is in contrast to most existing evacuation models (Abdelgawad and Abdulhai, 2010), focusing on evacuation process time manners. Such demand-based modelling is critical to the outcome and effectiveness of models in improving emergency response to bushfires in Australia. The novelty of these models to solve the evacuation problem include:

- The LEBMD-TW model considers capacitated multi-location, multi-routing, and multi-vehicle types (high and medium capacity vehicles).

- In the CMDVRP-TW model, an innovative capacitated vehicle-routing optimisation problem with time windows is formulated, enabling optimal generation of emergency evacuation response options and transportation priorities.
- The P-CMDVRP-TW model incorporates uncertainties in parameters (e.g., population, capacities, wildfire propagation constraints in real-time at escalating rates; gradual disruptions to shelter and road accessibilities; adverse time windows).
- The models simultaneously handle complex, multi-route, capacitated vehicle and multi-pick-up destinations, via multi-time windows utilising a VRP optimisation-modelling framework.

The next chapter develops solution approaches for the mathematical formulations developed in this chapter.

## Chapter 5

# Solution approaches

## 5.1 Introduction

This chapter develops the solutions to test as resolutions for the bushfire problem. Emergency response solutions to short-notice bushfire emergency evacuations under different disruption scenarios will be generated using the three solution approaches detailed in Chapter 4. The LEBMD-TW model uses a multi objective class of problem solving, requiring to be solved by the application of the Pareto front solutions. The $\varepsilon$-constraint, as one of the most common non-dominant solution approaches, is therefore implemented. In the next section, a novel heuristic solution approach to solve the second model, CMDVRP-TW is proposed. In order to evaluate the effectiveness of the proposed heuristic algorithm, a meta-heuristic genetic algorithm is designed, implemented and validated. This is followed by the proposal of an interactive solution fuzzy programming solution approach is solve the P-CMDVRP-TV model. In the final section, a summary of the solution approaches is presented.

## 5.2 Model I (*LEBMD-TW*): Late evacuation bushfire to multiple destinations with time windows

### 5.2.1 Epsilon-constraints method

In this study, the $\varepsilon$-constraint approach (Vira and Haimes, 1983, Coello et al., 2007) has been chosen as an efficient method to solve the research problem (Shahparvari et al., 2016a). Using the $\varepsilon$-constraint method, the main objective of the problem will be optimised while the remaining objectives are converted into inequality constraints, by assigning allowable levels of epsilon as upper or lower bound target values. All other objective functions will be minimised while constrained to the first objective function value. By varying the constraint boundaries, a rich representation of the efficient elements of the Pareto front can be obtained. This iteratively solves single-objective versions of the multi-objective problem, with an additional $\varepsilon$-constraint, in order to enumerate all Pareto-optimal solutions. In mathematical terms, when the decision-maker lets $f_n(x)$ be the objective function selected from among $N$ objective functions to be optimised, the multi-objective problem is transformed as follows:

$$
\begin{aligned}
&Max_{x\in\varphi} f_n(x) \\
&s.t. \qquad f_p(x) \geq \varepsilon_p \qquad \forall p \in \{1,2,\ldots,N\} \setminus \{n\}
\end{aligned}
\tag{5.1}
$$

Where, $\varphi$ defines the feasible solution space of the problem.

### 5.2.2 Solution framework

Algorithm 5.1 illustrates a general solution framework for the bi-objective optimisation problem (Shahparvari et al., 2016a). All Pareto-optimal solutions to a bi-objective minimisation problem are calculated and stored into set Z. The algorithm frequently runs in order to solve single-objective forms of the multi-objective problem computing all Pareto-optimal solutions. In each run, the Mixed-integer Multi Objective Problem (M.I.M.O.L.P) is solved for the first objective function $(f_1)$, using an additional constraint bounding the second objective $(f_2)$, the so-called as $\varepsilon$-constraint. The value of $\varepsilon$ is also considered small enough in comparison to the differences between the values of objective functions $f_1$ and $f_2$ along the Pareto front. Afterward, using the new found optimal value for $f_1$, $f_2$ is optimised. The generated Pareto-optimal solution is thus computed, and added to the solution set Z. The $\varepsilon$-constraint then is adjusted so that the next point to be compiled is optimal compare to all previous results regarding the second objective ($f_2$).

Algorithm 5.1 Bi-objective $\varepsilon$-constraint solution approach

```
Set
        ε − constraint ← f2 ≤ ∞
    Insert ε − constraint to M.I.M.O.L.P
While there is no feasible solution for M.I.M.O.L.P do:
  x ← Max(f1)
    Objective.Bound ← f1 = f1(x)
    Insert Objective.Bound to M.I.M.O.L.P
    x ← Min(f2)
    Z ← Z ∪ {x}
    Clear Objective.Bound from M.I.M.O.L.P
    Amend ε − constraint ← f2 ≤ f2(x) − ε
End while
Output: Set of Pareto-optimal solution Z
```

The main objective of the model is to evacuate the maximum number of people within the short time windows that are integral to bushfire scenarios. Therefore, the first objective $(f_1)$ is selected as the main objective to be optimised. While the second objective (minimising the resources), $(f_2)$, is converted into a hard constraint by applying the mentioned $\varepsilon$-constraint algorithm.

## 5.3 Model II (CMDVRP-TW): Capacitated multiple destinations vehicle routing problem with time windows

### 5.3.1 Heuristic algorithm

Finding an optimal solution is not an easy task and the use of traditional methods based on linear and nonlinear programming models is accompanied with heavy computing overhead. Having this in mind, an exact heuristic solution approach is developed here. Exact solutions of large-scale experiments are not practical, because the CMDVRP-TW model is a NP-hard problem. In order to ensure the applicability of the model to realistic case studies, this section develops a heuristic solution algorithm method to solve the model, as follows:

Algorithm 5.2 Heuristic solution algorithm

*n*=1;

While $\sum_{i\in I}\widetilde{D}_i > 0$,

**Solve the model**

$$\widetilde{D}_i \leftarrow \widetilde{D}_i - \sum_{m\in I}\sum_{i\in I}\sum_{(j,r)\in S_{i.}^{m}} X_{ijr}^{mn} V$$

$$\widetilde{C}_j \leftarrow \widetilde{C}_j - \sum_{m\in I}\sum_{i\in I}\sum_{(j,r)\in S_{i.}^{m}} X_{ijr}^{mn} V$$

$\mathrm{n} \leftarrow \mathrm{n}+1;$

End

"The number of vehicles" = *n*

A constructive heuristic algorithm is implemented to generate the routing plans, by individually assigning the required number of vehicles (Algorithm 5.2). That is, in the first step the algorithm assigns only one vehicle (*n=1*). The model prioritizes the assembly points based on pre-defined clearance and travel times, subsequently generating the first vehicle routing plan with the aim of maximising the total number of evacuees. Then, considering the total number of evacuees safely transported via vehicle number one, the algorithm updates the model with the remaining values of both evacuee population and shelter capacities. In the same way, the second vehicle (*n=2*) is assigned to travel among assembly points and shelters in order to transfer the maximum number of remaining evacuees within the clearance time. The proposed heuristic algorithm continues the assignment of vehicles until none of evacuee population remains. Therefore, the algorithm assigns vehicles and amends the parameters in order to determine the required number of vehicles. The next section presents a new designed meta-heuristic-based solution approach in order to evaluate the effectiveness of the proposed heuristic solution approach.

### 5.3.2 Meta-heuristic Genetic algorithm method

A designed genetic algorithm, as an alternative solution approach, is also utilised here to evaluate the performance of the results of proposed heuristic method. In this section, sets of 20 various randomly generated deterministic problems with different sizes are considered to solve and evaluate the performance of proposed model and solution approach. Input data are given in Table 5.1.

Table 5.1 Randomly generates parameters

| **Parameters description** | **Index** | **Applied values** |
|---|---|---|
| Number of townships | $I$ | Random~ Uniform [6, 25] |
| Number of shelters | $J$ | Random~ Uniform [5, 12] |
| Routes | $R$ | $(r_1, r_2, r_3)$ |
| Late evacuee population of each township | $D_i$ | Random~ Uniform [30, 500] |
| Shelter capacity | $V$ | 1000 |
| Time windows | $T_k$ | $({i_1}^{30"}, {i_2}^{60"}, {i_3}^{90"}, \dots, {i_{25}}^{750"})$ |
| Risk of disruption | $\mu_{ijr}$ | Random~ Uniform [0.15, 0.75] |
| Travel time | $t_{ijr}$ | Random~ Uniform [10, 60] |

The results are compared to results of applications of a designed genetic algorithm as another solution approach. The genetic algorithm, as an evolutionary optimisation algorithm, conducts a search through the space of solutions by exploiting a population of points in parallel rather than a single point. The overall developed genetic algorithm for the proposed model is outlined in Algorithm 5.3 as follows:

Algorithm 5.3 Genetic algorithm

| |
|---|
| Initialisation (set parameters, termination condition) |
| ***Repeat*** |
| *Vehicle# n=1* |
| ***Repeat*** (evolve solution $EP^n$ ) |
| Generate initial populations for $n$ (random EP solution) |
| Eliminate infeasible populations (solutions) (1) |
| Add new solution to $EP^n$ |
| Select two parents from the population |
| Crossover |
| Mutation |
| ***If*** the generated population is feasible ***then:*** |
| Evaluate fitness function (2) |
| Update $P_i$ and $C_j$ |
| ***Else*** regenerate the population |
| ***Until*** criteria are satisfied by chosen offspring |
| ***If*** $P_{left} = 0$, ***then*** replace offspring to $EP^n$ |
| ***Else*** *n=n+1* |
| ***Until*** stopping criterion is satisfied |

To apply the genetic algorithm approach all considered decision variables, i.e. $X_{ijr}^{mn}$ need to be coded to a data structure named a chromosome or a genome. The structure presented in Figure 5.1 is used for coding to represent the chromosomes. Each chromosome's length is equal to maximum number of trips a vehicle can travel. The evacuation mission length therefore is calculated by dividing maximum available time window by the shortest travel time of routes in the network. Each variant, or allele[6], represents an evacuation plan ( $X_{ijr}^{mn}$) and is limited to shelter capacities and time window constraints. To avoid the complexity of the development, no other array is considered for $\alpha_i^m$ and $\beta_i^m$ as its values can be calculated according to $X_{ijr}^{mn}$, i.e.: $if \sum_{m\in I}\sum_{i\in I}\sum_{(j,r)\in S_{i.}^m} X_{ijr}^{mn} > 0 \ then \ \alpha_i^m, \beta_i^m = 1, else = 0.$ For example, consider there are two affected cities and shelters with 2 numbered routes between each two points. Then the chromosome ($i_1$_1_$j_1$ _2_$i_1$_1_$j_2$) indicates that bus 1 starts the evacuation from

6 In genetic algorithm, each problem solver is a called *chromosome*. A position, or set of positions in a chromosome is called a *gene*. The possible set of alternative values of a *gene* are known as *alleles*. Each elective solution from pool of initial potential solutions (*population*) is called as *parent*. Elite *parents* then paired to reproduce set of new solutions called as new *children*.

township $i_1$ to shelter $j_1$ via route 1, then from $j_1$ to $i_1$ via route 2 and finally from $i_1$ to $j_2$ from route 1 and so on. For simplicity the chromosome is written as ($i_1$ _1_2_1) and denotes the route orders for the evacuation mission of bus 1.

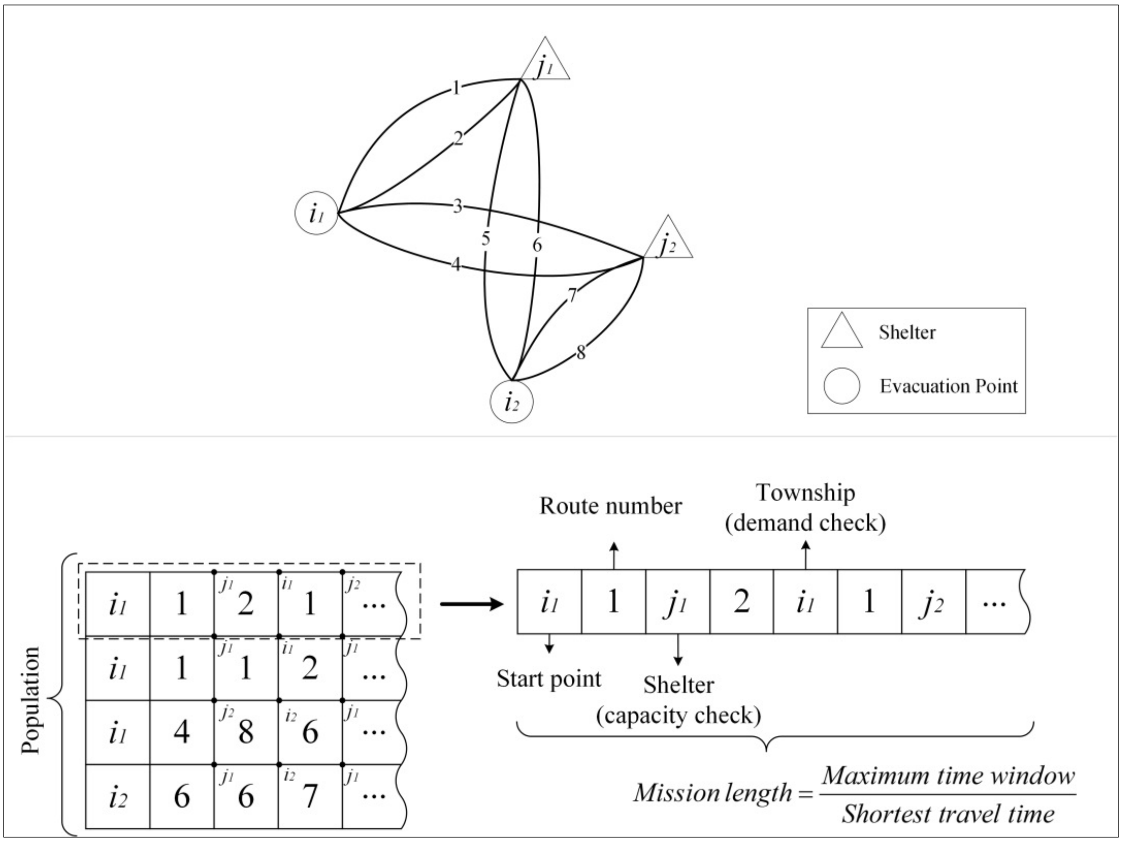



Figure 5.1 Chromosome presentation

The population elements (genomes) are completely defined by their strings: Population $=\{EP_1, EP_2, ..., EP_{popsize}\}$. The initial randomly generated population (potential solutions) is repeatedly undergoing a series of genetic operators (crossovers and mutations to generate new genomes, and selection and elitism to choose better genomes from the generated population) until new ‘‘better’’ genomes are produced (Deb et al., 2002, Saadatseresht et al., 2009, Li et al., 2010). In this research the multipoint binary mutation operator is used to switch bits in a genome according to a predefined mutation rate. Multipoint binary crossover operator is used, exchanging bits of two parent genomes according to a predefined crossover probability. It is notable that rates of mutation and crossover operators are defined at the discretion of decision maker. It is possible that the new children violate the constraints of the model.

A feasibility module is designed to check the feasibility of the generated population if the consequence of trips, routes and locations are possible in the network (equation 5.2). It turns 1 if there is a connection in the network from current location of a vehicle to its next destination, otherwise 0. Real solutions from the previous periods that are transformed to genomes can be added to the population.

$$\text{Feasible (Current location, egress route)} = \{0, 1\} \tag{5.2}$$

The quality of a genome is evaluated by the fitness function (Back, 1996). The fitness value of a genome reflects the quality of the coded solution and is produced by the fitness function given the actual values of decision variables and constraints coded in the genome (Bäck et al., 1997).

The fitness values of genomes leading to solutions with higher profit will have lower values. In this study, the fitness value is calculated by the sum of the left over population and a penalty term of route capability violations. The fitness function (to be minimised, i.e. lower values represent better solutions) is calculated on the basis of forecast values of demand as follows:

$$k_1 P_{left} + \sum_{i=1}^{c.l.} \frac{k_2}{1 - \mu_i} \tag{5.3}$$

where $P_{left}$ defines the left over late evacuee population that could not be transferred by the assigned vehicle. The second term, as a penalty function, calculates the entire risk of assigned routes to be maximised. $k_1$ and $k_2$ are utilised as auxiliary coefficients in the weighted sum method, and are selected in the range of [0-1], summing to one to represent the weight of impression for each parameter. Note that in the considered case, the better genomes are those with lower fitness function value and the G.A is designed to search to minimise the fitness function.

The generation of the initial solutions will keep on evolving until the specified stopping condition has been fulfilled. In this research, the termination criterion monitors improvement from generation to generation. The algorithm stops when there is no change in the best objective function and restores the best current solution from the chosen population of genomes.

In this research, the following parameters are used in the of GA experiments: size of population: 100 (or 50), number of parent genomes to pass to next generation: 5, number of randomly chosen genomes added to next generation: 0 (or 5), number of generations: 10,000, probability of binary multipoint mutation: 0.05, probability of binary multipoint crossover: 0.25.

### 5.3.3 Validation

In order to provide an appropriate result in GA each problem is run five times. Also, each problem applied to the heuristic algorithm is run by the application of two commercial solvers as CPLEX and Gurobi. Then, three factors including best solution, average solution and average related percentage deviation ($\overline{RPD}$) index in each of the five runs are considered to provide a comprehensive comparison of the algorithms results. The following equation defines how the $\overline{RPD}$ is calculated:

$$\overline{RPD} = \sum_{i=1}^{R} \frac{\left(\frac{B-U_i}{B}\right)}{R} \times 100 \tag{5.4}$$

Where $R$, $B$, and $U_i$ represent the number of iterations for each set, the best result in all runs, and the result of algorithm in the $i^{\text{th}}$ run, respectively. The results of this application are shown in Table 5.2.

The results in Table 5.2 show that the exact method is only capable to solve small size problems, obviously due to complexity of the problems. On the other hand, the results show that the proposed heuristic algorithm has less $\overline{RPD}$ than the Meta-heuristic algorithm in all the 20 sets of problems. The maximum $\overline{RPD}$ for heuristic approach is 0.259 and, on average, is 0.123 which means that this approach can find solutions that are more appropriate than the GA method. Also, the heuristic approach provided better solutions than the genetic algorithm for best solution and average solution, even considering the increase in the number of variables in all of the generated problems.

Table 5.2 Results of both Heuristic and Meta heuristic solution approaches

| Set no. | I | J | Exact solution Best | Average | $\overline{RPD}$ | Heuristic Best | Average | $\overline{RPD}$ | GA Best | Average | $\overline{RPD}$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 6 | 5 | 0.695 | 0.695 | 0 | 0.695 | 0.695 | 0 | 0.695 | 0.695 | 0 |
| 2 | 9 | 6 | | - | | 0.833 | 0.801 | 0.259 | 0.772 | 0.749 | 0.265 |
| 3 | 9 | 8 | | - | | 0.831 | 0.782 | 0.135 | 0.792 | 0.779 | 0.135 |
| 4 | 10 | 8 | | - | | 0.706 | 0.653 | 0.168 | 0.653 | 0.643 | 0.156 |
| 5 | 10 | 8 | | - | | 0.801 | 0.782 | 0.079 | 0.752 | 0.72 | 0.109 |
| 6 | 12 | 5 | | - | | 0.814 | 0.762 | 0.213 | 0.752 | 0.746 | 0.218 |
| 7 | 12 | 8 | | - | | 0.734 | 0.702 | 0.108 | 0.693 | 0.696 | 0.135 |
| 8 | 12 | 10 | | - | | 0.854 | 0.801 | 0.187 | 0.811 | 0.802 | 0.198 |
| 9 | 14 | 5 | | - | | 0.829 | 0.792 | 0.119 | 0.831 | 0.777 | 0.126 |
| 10 | 14 | 7 | | - | | 0.668 | 0.633 | 0.177 | 0.633 | 0.615 | 0.215 |
| 11 | 18 | 5 | | - | | 0.648 | 0.603 | 0.15 | 0.623 | 0.604 | 0.18 |
| 12 | 18 | 9 | | - | | 0.779 | 0.712 | 0.159 | 0.742 | 0.724 | 0.194 |
| 13 | 18 | 10 | | - | | 0.66 | 0.633 | 0.101 | 0.633 | 0.607 | 0.121 |
| 14 | 20 | 5 | | - | | 0.766 | 0.702 | 0.168 | 0.742 | 0.731 | 0.197 |
| 15 | 20 | 12 | | - | | 0.847 | 0.782 | 0.026 | 0.792 | 0.761 | 0.121 |
| 16 | 23 | 6 | | - | | 0.646 | 0.613 | 0.139 | 0.653 | 0.597 | 0.201 |
| 17 | 23 | 8 | | - | | 0.751 | 0.712 | 0.027 | 0.722 | 0.717 | 0.113 |
| 18 | 23 | 11 | | - | | 0.657 | 0.623 | 0.163 | 0.663 | 0.654 | 0.196 |
| 19 | 25 | 5 | | - | | 0.833 | 0.782 | 0.063 | 0.801 | 0.784 | 0.088 |
| 20 | 25 | 12 | | - | | 0.742 | 0.712 | 0.018 | 0.712 | 0.676 | 0.091 |
| Average RPD% | | | | - | | 0.123 | | | 0.153 | | |

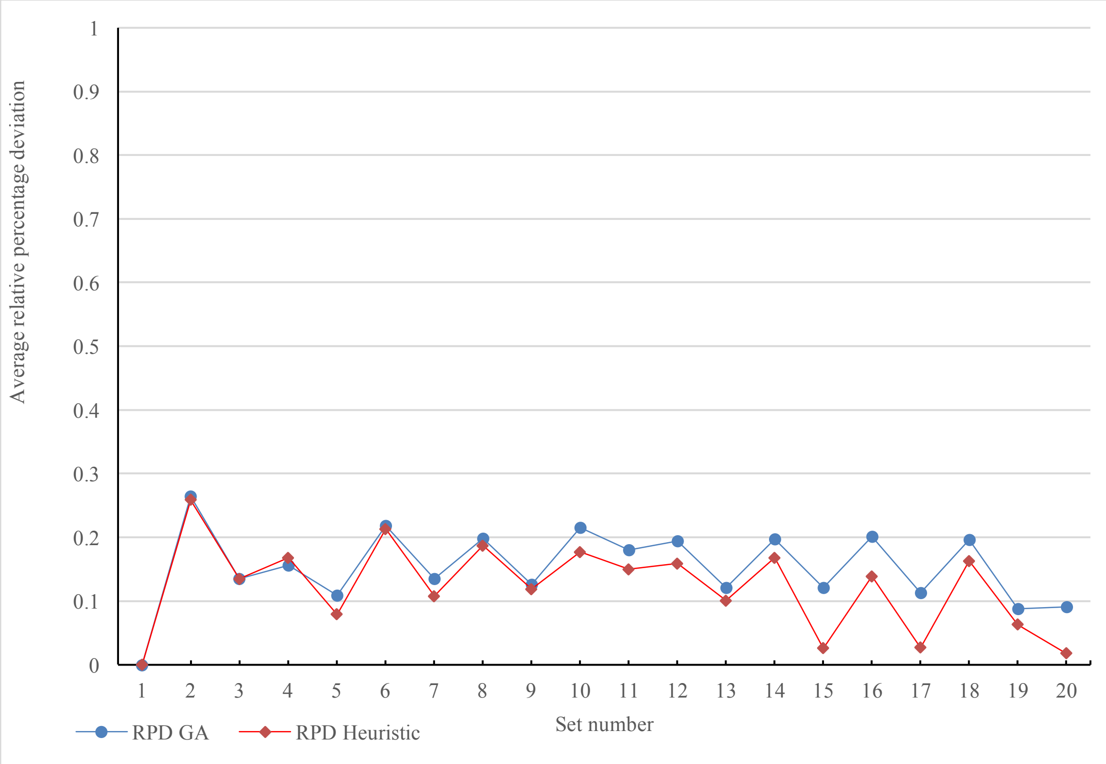



Figure 5.2 Comparison of the RPD factors for G.A and Heuristic algorithms

In addition to the data shown in Table 5.2, values of the RPD factor obtained in successive generations were extracted and graphed (Figure 5.2). The graph clearly demonstrates the effectiveness of the heuristic algorithm in providing better results in most the problems.

## 5.4 Model III (P-CMDVRP-TW): Possibilistic capacitated multiple destinations vehicle routing problem with time windows

### 5.4.1 Interactive fuzzy programming

Decision-making in a complex network, such as that which is likely to exist in a natural disaster emergency response scenario, requires the consideration of both conflicting objectives and different constraints. In addition most of the parameters embedded in such problems are often fuzzy and can therefore only be estimated subjectively, because of the incompleteness and/or unavailability of necessary data (Chen and Chang, 2006, Wang and Liang, 2005). For example, evacuee demands, emergency evacuation response cost/time coefficients and the amount of available resources are often imprecise, and therefore it is not appropriate to assign a crisp set of values to these ambiguous parameters. Instead possibility theory is utilised in order to formulate the fuzziness. Possibility distributions cater for the ambiguous problem parameters (Liang, 2006, Wang and Liang, 2005).

Different approaches have been developed in the existing emergency evacuation research literature in order to solve the problem summarised in Chapter 3. These approaches include the max–min approach (Zimmermann, 1978), the augmented max–min approach (Lai and Hwang, 1992), , the two-phase fuzzy approach (Li et al., 2006), the modified version of Werner's approach (Selim and Ozkarahan, 2008), and the single-phase interactive fuzzy approach (Torabi and Hassini, 2008). The solutions obtained by the max–min approach might not be efficient or unique; the augmented max–min method sometimes generates inefficient solutions that are dominated by the solutions of the two-phase fuzzy approach, and the modified version of Werner's method usually yields an efficient but poorly compromised and unbalanced solution (Torabi and Hassini, 2008). In comparison to the two-phase fuzzy approach, the single-phase interactive approach (Torabi and Hassini, 2008) does not suffer from the these deficiencies and requires less computational effort. This method requires positive and negative ideal solutions to be specified first. In order to determine the ideal positive and negative solution for each objective function, the formulation should be transformed as below:

$$Z_1^{PIS} = MaxZ^m, \qquad Z_1^{NIS} = MinZ^m \tag{5.5}$$

$$Z_2^{PIS} = Min(Z^m - Z^p), \qquad Z_2^{NIS} = Max(Z^m - Z^p) \tag{5.6}$$

$$Z_3^{PIS} = Max(Z^o - Z^m), \qquad Z_3^{NIS} = Min(Z^o - Z^m) \tag{5.7}$$

In addition, the corresponding linear membership function of each new objective function of the auxiliary multi-objective linear problem is represented by:

$$f_1(Z_1) = \begin{Bmatrix} 1 & if\ Z_1 > Z_1^{PIS} \\ \dfrac{Z_1 - Z_1^{PIS}}{Z_1^{PIS} - Z_1^{NIS}} & if\ Z_1^{NIS} < Z_1 < Z_2^{PIS} \\ 0 & if\ Z_1 < Z_1^{NIS} \end{Bmatrix} \tag{5.8}$$

$$f_2(Z_2) = \begin{Bmatrix} 1 & if\ Z_2 < Z_2^{PIS} \\ \dfrac{Z_2^{NIS} - Z_2}{Z_2^{NIS} - Z_2^{PIS}} & if\ Z_2^{PIS} \le Z_2 \le Z_2^{PIS} \\ 0 & if\ Z_2^{NIS} < Z_2 \end{Bmatrix} \tag{5.9}$$

$$f_3(Z_3) = \begin{Bmatrix} 1 & if\ Z_3 > Z_3^{PIS} \\ \dfrac{Z_3 - Z_3^{NIS}}{Z_3^{PIS} - Z_3^{NIS}} & if\ Z_3^{NIS} \le Z_3 \le Z_3^{PIS} \\ 0 & if\ Z_3 < Z_3^{NIS} \end{Bmatrix} \tag{5.10}$$

The overall satisfaction compromise solution is obtained using the following auxiliary crisp formulation (Torabi and Hassini, 2008):

$$\begin{aligned} & Max\ \lambda = \gamma\lambda_0 + (1-\gamma) \times \sum_h \psi_h f_h(Z_h) \\ & s.t. \\ & \qquad \lambda_o \le f_h(Z_h), \qquad\qquad h = 1,2,3; \\ & \qquad \sum_h \psi_h = 1, \\ & \qquad \lambda_0, \gamma \in [0,1], \\ & \qquad and\ \psi_h > 0 \end{aligned} \tag{5.11}$$

where the auxiliary variable $\lambda_0$ and parameters $\psi_h$ and γ respectively represent the decision-maker's overall degree of satisfaction with the determined objective values, the relative importance of the objective function, and the coefficient of compensation. The advantage of this formulation is in aggregating the overall degree of satisfaction of objectives, $\lambda_0$, the weighted sum of these achievement degrees $f_h(Z_h)$. $\psi_h$ is determined by the decision-maker and γ controls the degree of compromise among the objectives, enabling the formulation mentioned above to achieve both balanced and unbalanced compromised solutions. Finally, the proposed heuristic method described in Section 5.3.1 is applied to solve the proposed auxiliary crisp model (equation 5.12).

## 5.5 Summary

This chapter presented solutions approaches to solve the formulations described in Chapter 4. Due to the multi-objective nature of problem formulations, it is not possible to provide the decision maker with a single "optimal" solution. However, by filtering out so-called dominated solutions, the choice can be restricted to a small number of promising solution candidates. The Ɛ-constraint method therefore utilised for solution approach of the LEBMD-TW model.

The exact solution of the CMDCRP-TW model is not feasible in the large size problems (NP-Hard). Hence, a heuristic solution method was developed to tackle the complexity associated with Vehicle Routing Problem (VRP)-based problems. The effectiveness of a heuristic algorithm solution was compared and evaluated with a designed Meta-heuristic genetic algorithm using sets of numerical examples.

To solve the P-CMDVRP-TW model, the possibilistic model was first converted into an auxiliary crisp multi-objective model. An interactive fuzzy approach was applied to transformed multi-objective problem into an equivalent single-objective model. Finally, the Heuristic approach, which was applied to the CMDCRP-TW model, was also implemented and applied to P-CMDVRP-TW to achieve the overall satisfactory compromise solution.

In the next chapter, these three short-notice evacuation models with different approaches will be applied on a real case study of the 2009 Black Saturday bushfires.

# Chapter 6

# Results & Analysis

## 6.1 Introduction

This chapter applies the short-notice evacuation models to generate evacuation plans in three bushfire scenarios, described in the previous two chapters. The validity and sensitivity of the models are also tested. Each model is validated as a small case study in Lake Eildon Park section of the case study area. These models are further applied at the Marysville bushfire on the 2009 Black Saturday bushfires. The results of these models are discussed to help generate evacuation plans. The plans are structured into four components including evacuation of late evacuees, shelter assignment, routing and fleet scheduling. Overall, this chapter addresses the last three research questions:

- What is the optimum allocation of shelters required to maximise spatial coverage of late evacuees in bushfire affected area?;
- How can the most efficient routes (i.e. safest and shortest) be determined to transfer people from assembly points to designated shelters?; and
- How can vehicle assignment and scheduling be optimised to maximise short notice evacuation within a specified time window?

In the final section, a summary of the chapter is provided.

## 6.2 Model I: LEBMD-TW

### 6.2.1 Validation: application on small size case study (Lake Eildon Park)

The main aim of this section is to demonstrate how the proposed mathematical formulation can be utilised to improve the performance of the evacuation process in an emergency situation to increase the numbers of saved lives. Therefore, a real case study in three bushfire scenarios was examined to demonstrate the problem methodology. Also, sensitivity analysis against changing the key parameters such as number of required vehicles and number of assigned shelters was undertaken. In addition, shelter capacity usage in each scenario is investigated is this section. The model was implemented using the CPLEX solver 12.6 (CPLEX, 2005).

#### 6.2.1.1 Case Study: Lake Eildon National Park

The developed model is applied to a case study of a bushfire prone area in Northeast of Victoria in Australia. The area of study contains six townships (Eildon, Thornton, Mainton, Alexandra, Acheron, and Bonnie), which are located near the Lake Eildon national park. With a total population of about 1036 people, this hilly region is thus not densely populated. Based on the analysis carried out by CFA, approximate one-third (33 per cent) of residents were affected by the Black Saturday Bushfires, majority of which could be deemed late evacuees (Teague et al. 2009). Four potential safer townships (i.e. Taggerty, Merton, Yarck, and Yea) are nominated by CFA to shelter late evacuees during an emergency evacuation situation. Shelters are assumed to have a finite capacity to accommodate evacuees (Table 6.1) (e.g. the Merton public cricket ground oval can shelter 450 persons).

Real transportation network and travel time between the townships are computed. Therefore, the travel time between any two nodes the network is calculated based on real distances and travel speed zones. Shelters availability and roads connectivity are affected by the direction and path of bushfires. Hence, time windows are defined to prioritise the bushfire arrival time.

Time windows are calculated on the basis of wind direction and distance between bushfire ignition point and townships using the average bushfire spread rate, which is approximately 20 kilometres per hour (Teague et al. 2009). Also, two different types of vehicles (Bus can carry 40 and Van 10 people) are incorporated. For the base case, 20 buses and 30 vans are available to be assigned to gain the optimal routing process. Also, to balance vehicles assignment, a usage cost for each type of vehicle is considered as 100 financial units for bus and 40 for the van.

Table 6.1 Summary of inputs and assumptions

| | Townships (origins) | Population (numbers) | Time Windows (mins) | | Shelters (destinations) | Capacity (number) | Traversal Time (mins) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | $j_1$ | $j_2$ | $j_3$ | $j_4$ |
| $i_1$ | Bonnie | 171 | 150 | $j_1$ | Taggerty | 350 | $i_1$ | 28.8 | 14.4 | 24.6 | 31.2 |
| $i_2$ | Mainton | 29 | 90 | $j_2$ | Merton | 450 | $i_2$ | 18 | 27.6 | 17.4 | 18 |
| $i_3$ | Alexandra | 398 | 105 | $j_3$ | Yarck | 500 | $i_3$ | 10.8 | 20.4 | 10.2 | 10.8 |
| $i_4$ | Acheron | 96 | 120 | $j_4$ | Yea | 500 | $i_4$ | 4.8 | 26.4 | 16.2 | 16.8 |
| $i_5$ | Thornton | 121 | 75 | | | | $i_5$ | 7.2 | 28.2 | 18 | 18.6 |
| $i_6$ | Eildon | 221 | 30 | | | | $i_6$ | 15.6 | 34.8 | 24.6 | 25.2 |

### 6.2.1.2 Development of bushfire scenarios for validation

Three comprehensive *What-If* bushfire scenarios are generated to better evaluate the model. It ranges from a simple through to more complex bushfire scenarios. Table 6.2 describes the considered bushfire scenarios.

Table 6.2 Bushfire What-If scenarios for validation of the first model

| Bushfire scenario | Severity | Wind direction and road conditions | Road disruptions |
|---|---|---|---|
| **Bushfire scenario 1** | Low | South-eastern to north-western wind direction spreads the bushfire and disrupts 2 roads | $i_1 \rightarrow j_1$ (Northern Mainton Rd)<br>$i_6 \rightarrow j_2$ (Back Eildon Rd) |
| **Bushfire scenario 2** | Medium | Wind direction changes to East – west and restricts 4 main roads | $i_1 \rightarrow j_1$ (Northern Mainton Rd)<br>$i_2 \rightarrow j_2$ (Southern Mainton Rd)<br>$i_5 \rightarrow j_4$ (Goulburn Valley Hwy)<br>$i_6 \rightarrow j_2$ (Back Eildon Rd) |
| **Bushfire scenario 3** | High | Bushfire Spotted in three different points and as a result of a north-eastern to south-western wind direction, 7 roads are disconnected | $i_1 \rightarrow j_1$ (Northern Mainton Rd)<br>$i_1 \rightarrow j_2$ (Maroondah Hwy)<br>$i_2 \rightarrow j_3$ (Southern Mainton Rd)<br>$i_2 \rightarrow j_4$ (Mainton Rd)<br>$i_5 \rightarrow j_1$ (Taggerty-Thornton Rd)<br>$i_5 \rightarrow j_2$ (Goulburn Valley Hwy)<br>$i_6 \rightarrow j_2$ (Back Eildon Rd) |

*Scenario 1: South-eastern to north-western wind restricts 2 roads*

In the simplest scenario, a bushfire is ignited in the 10 km vicinity of Eildon township ($i_1$) propagated in the network and has disrupted Northern Mainton road and Back Eildon road as the traversal route between Bonnie ($i_1$) to Taggerty ($j_1$) and Eildon ($i_6$) to Merton( $j_2$) (Figure 6.1). All shelters are assumed to be available. Hence, considering bushfire spread direction and speed, Eildon late evacuee population (221 people) must to be evacuated to the nearest and safest shelter within the 45 Minutes as other township evacuation demands must be evacuated before bushfire invasion.

*Scenario 2: East to west wind restricts 4 roads*

In this scenario it is assumed that the bushfire has propagated slightly faster than the previous prediction of spread area, which is culminated into more disruptions in the network infrastructure. Mainton road (Northern and Southern part), Back Eildon road are considered not to be longer available. Also Goulburn Valley highway as one of key routes in the Eildon network is assumed to be disrupted by bushfire propagation (Figure 3). Therefore, transportation routes between Eildon ($i_6$) and Mainton ($i_2$) to Merton ( $j_2$), Bonnie ($i_1$) and Thornton ($i_5$) to Yea ($j_4$) are not longer available.

*Scenario 3: North eastern to south western wind restricts 7 roads*

As the most complex scenario of this study, the bushfire is assumed to disrupt 7 main links in the transportation network. Beside the pervious disruptions, it has assumed that the bushfire has propagated and disrupted the Maroondah highway major traversal link in the network. Also, the Taggerty-Thornton road is affected by the bushfire. Therefore, Evacuee are not able to be transferred between Bonnie ($i_1$) and Thornton ($i_5$) to Taggerty ($j_1$), Bonnie ($i_1$), Thornton ($i_5$) and Eildon ($i_6$) to Merton ($j_2$). Respectively, Mainton ($i_2$) people cannot be evacuated to Yarck ($j_3$) and Yea ($j_4$). To investigate the impact of bushfire road disruptions on the optimal evacuation process plan, all the other input dataset assumptions are considered to be same as previous scenarios.

Also Figure 6.1 illustrates the scenarios accompanied by bushfire isochrones to show the bushfire-spread scenarios pertaining to the evacuation time windows based on wind direction and bushfire severity.

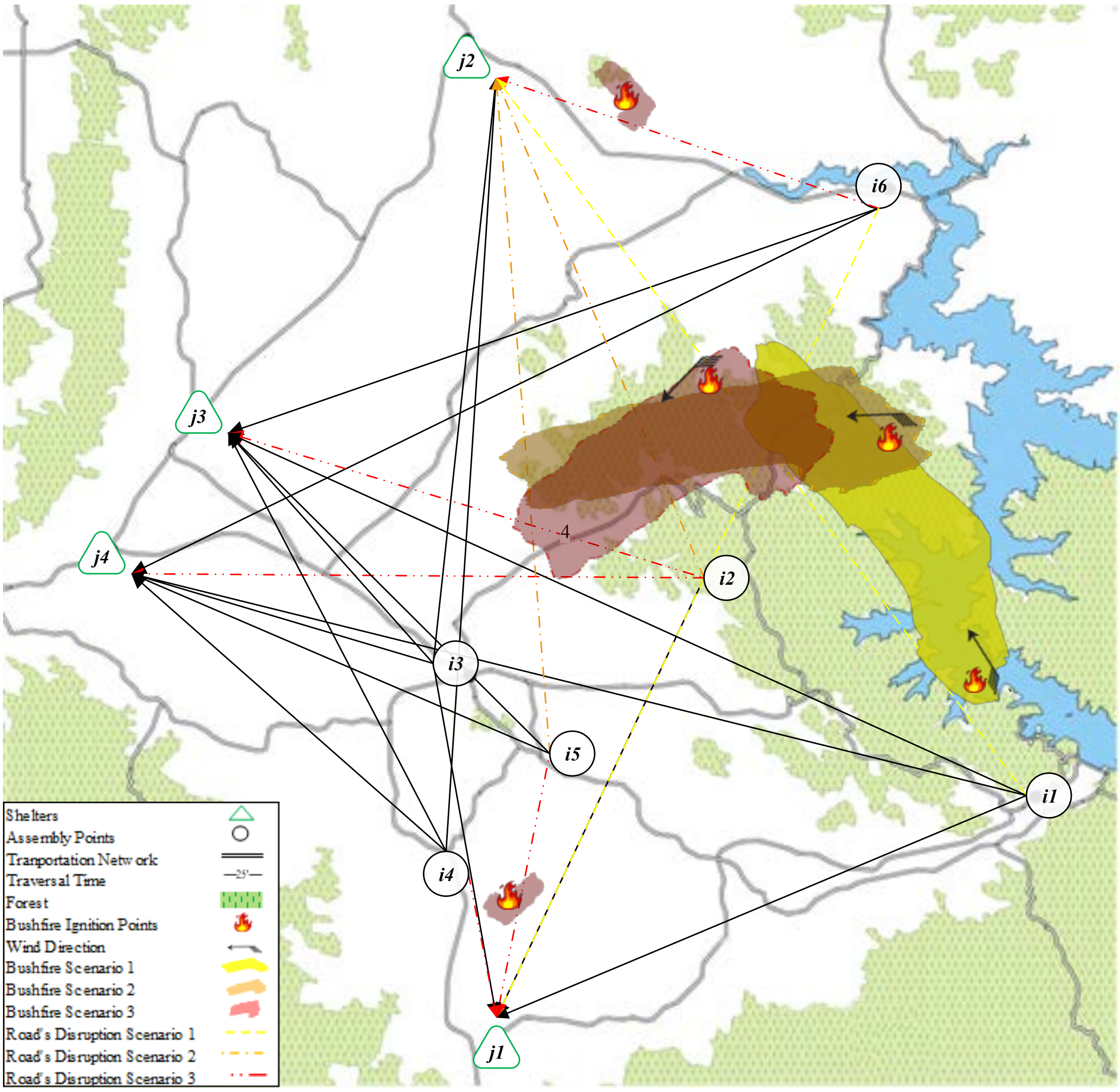



Figure 6.1 Illustration of bushfire What-IF scenarios (source: Shahparvari et al. (2015d)).

In Figure 6.1, three bushfire scenario are shown in different colours (Scenario 1: yellow, Scenario 2: orange, Scenario3: red). Respectively, the disrupted routes are depicted by dashed lines with the same colours.

According to the proposed epsilon solution approach described in Chapter 5, In this model (LEBMD-TW) the main objective is set to save more human lives and evacuate more people within the time windows. Therefore, the first objective $f1$ is chosen as the main objective to be optimised, while, $f2$ as the second objective is converted into a hard constraint by application of the Ɛ-constraint method (Shahparvari et al., 2015d). Respectively in the next step, the second objective function will be minimised to determined number of required available recourses as shelters and rescue vehicles. The outputs are as follows:

#### 6.2.1.3 Output of validation

***Step 1: Preliminary number of available resources (shelters and rescue vehicles)***

The objective value for the first step solution is 87.9 which represents the minimised cumulative value of assigning facilities and resources to entirely evacuate evacuees. Also, the preliminary output of in this step indicates that all 4 available shelters ($j_1$, $j_2$, $j_3$, and $j_4$) should be utilised to cover the evacuation demand of late evacuee population within the time windows. Results of the analysis show that at least 23 rescue vehicles including 13 Buses and 10 Vans are required to transfer all evacuees. In this case study, the optimal output was obtained by assuming 0.95 for parameter $w_1$and 0.05 for $w_2$. Obviously the higher assigned value for $w$ lead to stronger impact of the associated parameter in the model.

***Step 2: Optimal number of shelters, vehicles and routing***

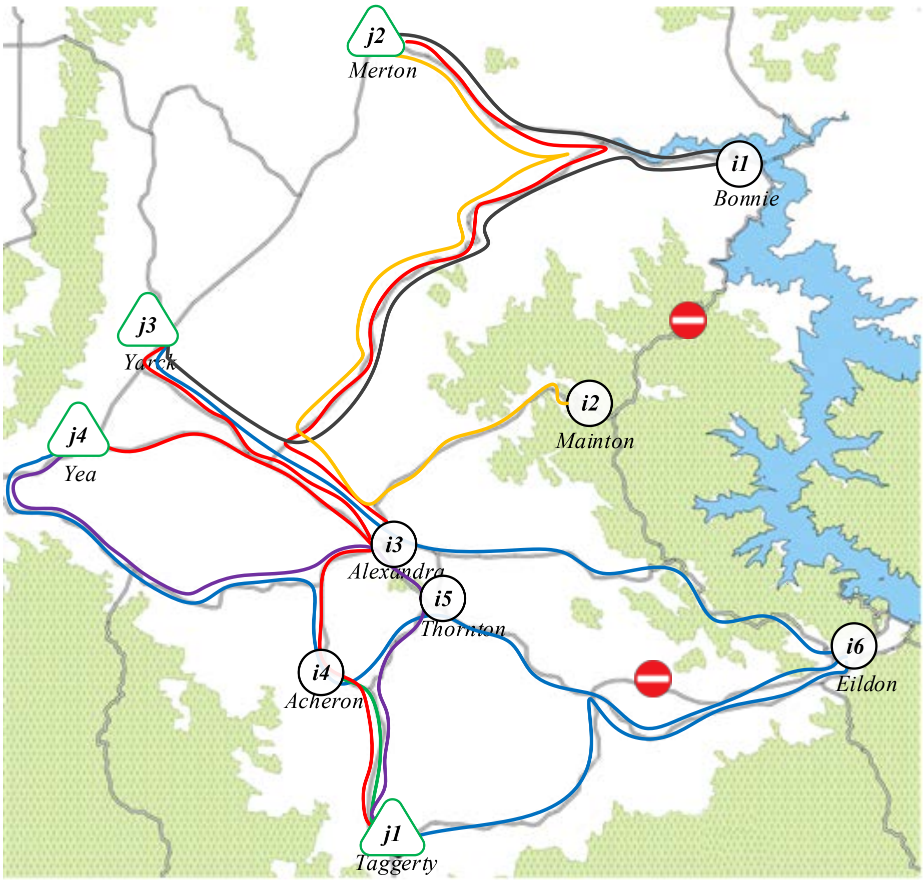
*Optimal evacuees' transportation to the assigned shelters:*

In this step, the model is solved while it is constrained to the preliminary values of the required resources that was achieved in the first step. Table 6.3 represents the optimal distribution of evacuees within the accessible routes in transportation network in each scenario. Respectively, Table 6.3 represents the optimal assignment of the required vehicles followed by the number of required trips to evacuate the evacuee population.

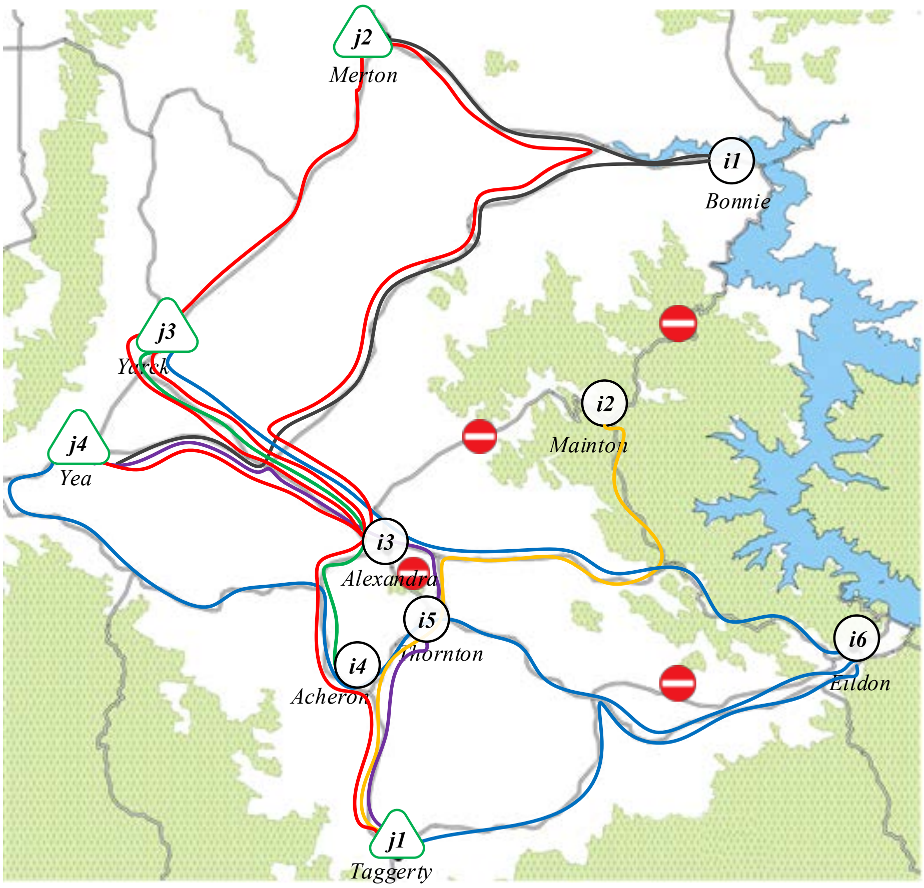
Table 6.3 Optimal evacuees' distribution to the assigned shelters

| | **Bushfire Scenario 1 Low Intensity** | | | | **Bushfire Scenario 2 Medium Intensity** | | | | **Bushfire Scenario 3 High Intensity** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Evacuated people** | $j_1$ | $j_2$ | $j_3$ | $j_4$ | $j_1$ | $j_2$ | $j_3$ | $j_4$ | $j_1$ | $j_2$ | $j_3$ | $j_4$ |
| $i_1$ | 0 | 100 | 71 | 0 | 0 | 100 | 0 | 71 | 0 | 0 | 100 | 71 |
| $i_2$ | 0 | 29 | 0 | 0 | 29 | 0 | 0 | 0 | 29 | 0 | 0 | 0 |
| $i_3$ | 100 | 100 | 100 | 98 | 100 | 100 | 100 | 98 | 100 | 100 | 100 | 98 |
| $i_4$ | 96 | 0 | 0 | 0 | 0 | 0 | 96 | 0 | 0 | 0 | 96 | 0 |
| $i_5$ | 52 | 0 | 0 | 69 | 100 | 0 | 0 | 21 | 0 | 0 | 41 | 80 |
| $i_6$ | 76 | 0 | 97 | 48 | 100 | 0 | 21 | 100 | 100 | 0 | 97 | 24 |
| **Used Cap** | 324 | 229 | 268 | 215 | 329 | 200 | 217 | 290 | 229 | 100 | 434 | 273 |
| **Shelters Assignment** | $j_1$ | $j_2$ | $j_3$ | $j_4$ | $j_1$ | $j_2$ | $j_3$ | $j_4$ | $j_1$ | $j_2$ | $j_3$ | $j_4$ |
| | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

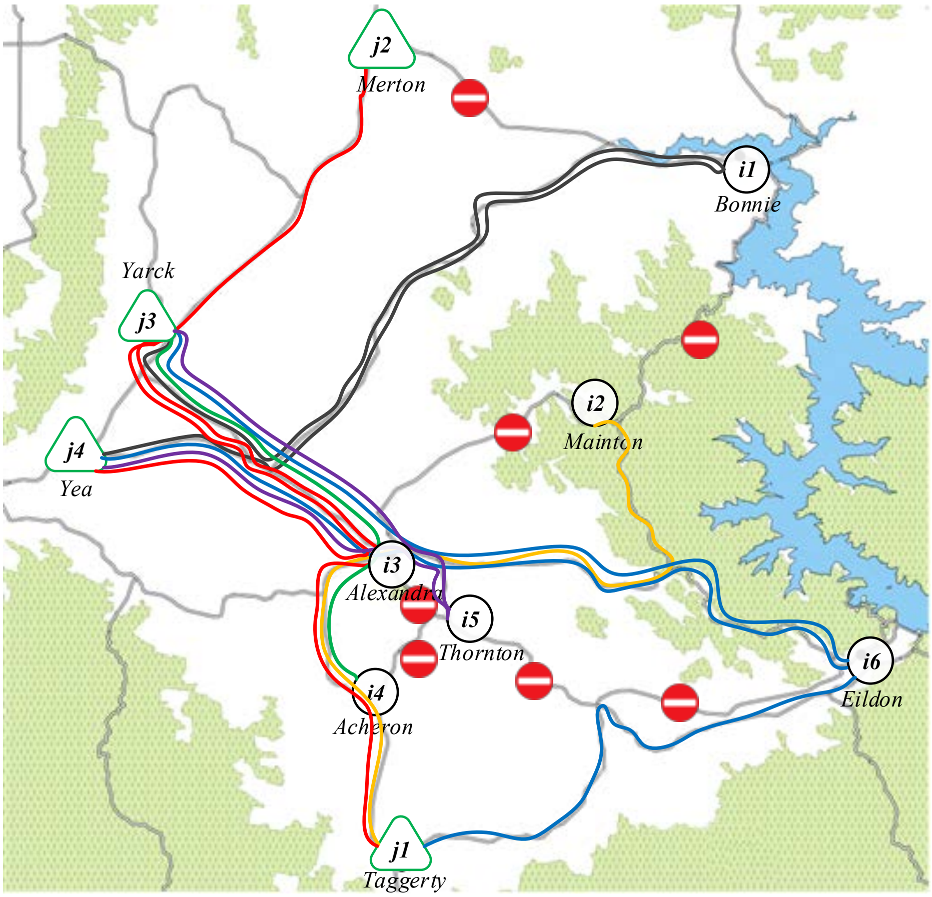
As it is shown in Table 6.3, Eildon ($i_6$) has the minimum time window and people should be evacuated within 30 minutes before bushfire reaches there. Therefore, in bushfire scenario 1, Merton ($j_2$) is not accessible and there is no transportation to there. The optimal plan for this township is to transfer 76 people to Taggerty ($j_1$), 97 people to Yarck ($j_3$) and the rest of the 48 evacuees to Yea ($j_4$). In the second scenario, bushfire intensity is medium and the Goulburn Valley Highway and Mainton Road also are blocked. Regarding the new road disruptions and scenario's constraints as time windows, shelter capacities and vehicles availability, the optimal emergency evacuation plan is to evacuate 100 people to shelter $j_1$, 21 people to $j_3$ and the rest of 100 people to shelter($j_4$). Respectively, the optimal evacuation routing plans for other hazardous townships are presented in Table 6.3. Also, Figure 6.2 visualises the optimal emergency evacuation routing and distribution of late evacuees in each scenario. The optimal evacuation route for each assembly point is illustrated by a specific colour (Bonnie: black, Mainton: orange, Alexandra: red, Acheron: green, Eildon: blue). The number of evacuated people by each route is also shown in Table 6.3.




**Bushfire Scenario 1**




**Bushfire Scenario 2**




**Bushfire Scenario 3**

Figure 6.2 Optimal routing of evacuees' distributions from the affected areas to shelters in three bushfire scenarios.

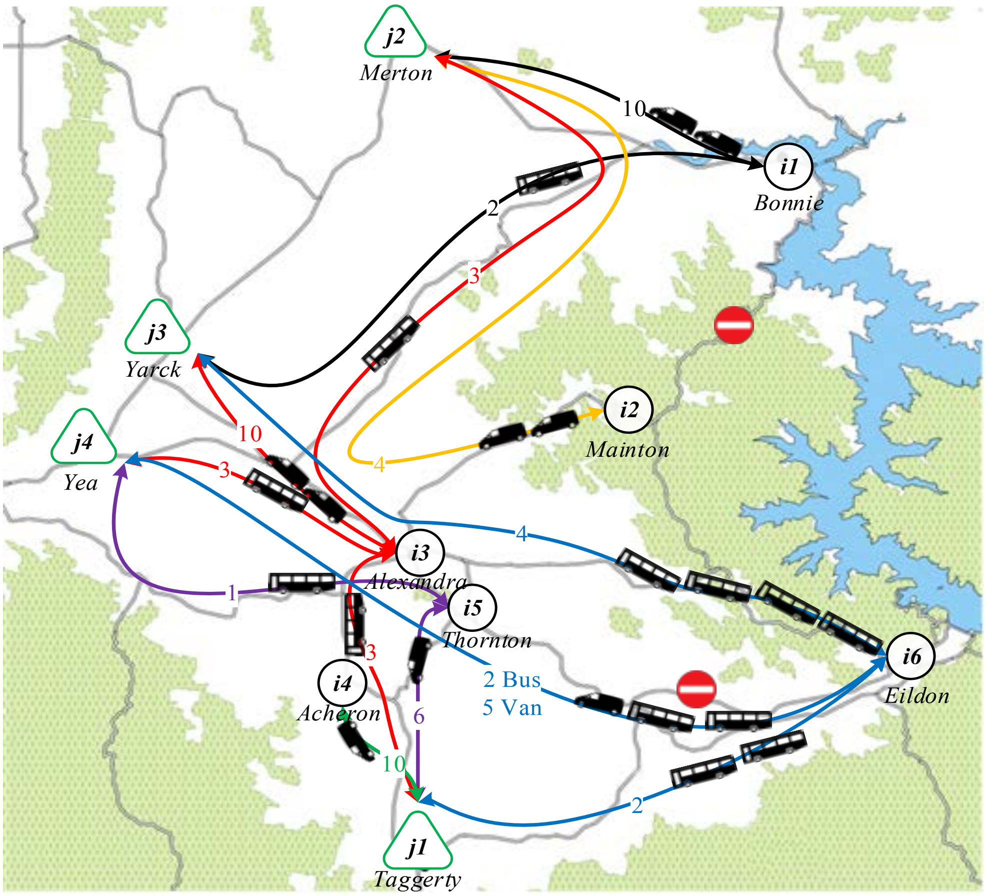
*Optimal number of assigned rescue vehicles and trips:*

Table 6.4 represents the optimal assignment of vehicles and number of trips that are required to evacuate the late evacuee population. For example, in scenario 1, Eildon has the shortest time window. Therefore, 2 buses are assigned to transfer 76 evacuees from Eildon ($i_6$) to Taggerty ($j_1$). Accordingly, 97 people are transported to Yarck ($j_3$) by 4 buses in one-way trips and the rest of the 48 evacuees are evacuated by assignment of 2 buses and 1 van traveling between 1 and 5 times between Eildon ($i_6$) and Yea ($j_4$) simultaneously to transfer Eildon population within the 45 minutes predefined time window. The results suggest that, due to the predefined route disruption in the Northern Mainton road, evacuees could not be transferred to Merton ($j_2$). In scenario 2, 100 people are evacuated to Taggerty ($j_1$) by assignment of 3 buses trips 3 times while 1 bus is assigned to serve the evacuation process from $i_6$ to $j_3$.

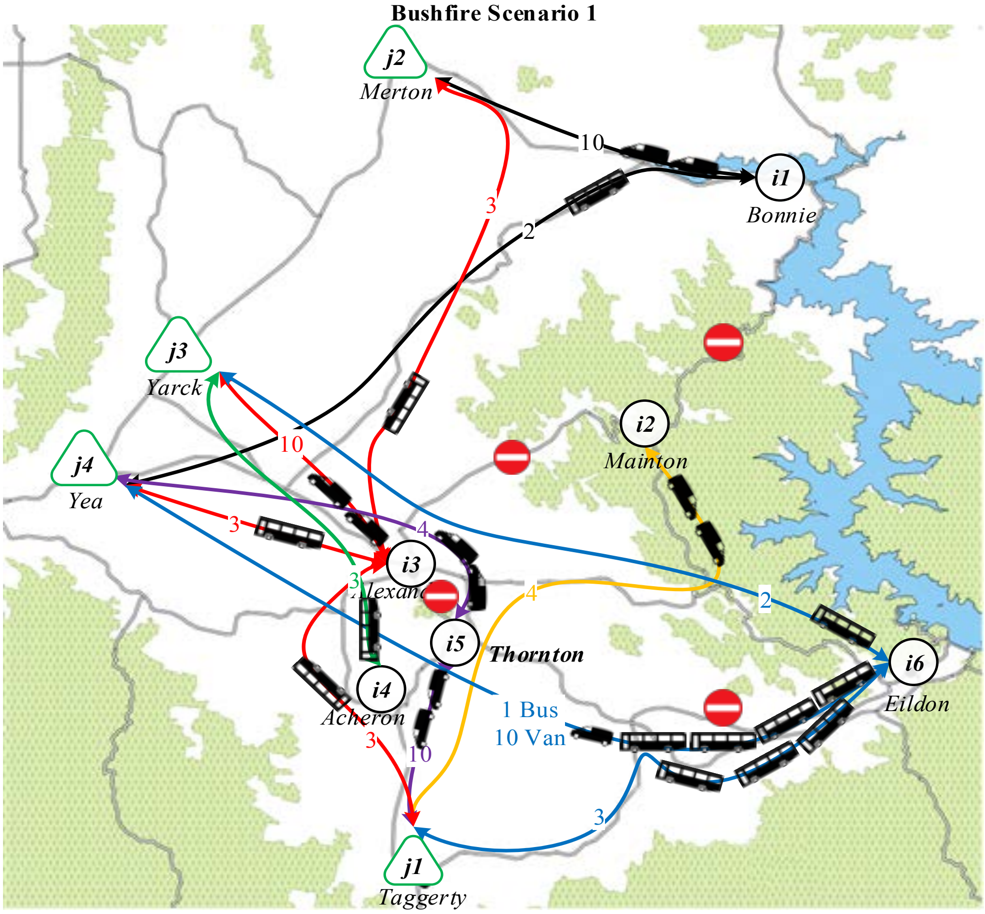
Table 6.4 Optimal assignment of rescue vehicles and number of trips (B = Bus, V= Van)

| | **Bushfire scenario 1 Low intensity** | | | | **Bushfire scenario 2 Medium intensity** | | | | **Bushfire scenario 3 High intensity** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Number of vehicles | | | | Number of vehicles | | | | Number of vehicles | | | |
| | $j_1$ | $j_2$ | $j_3$ | $j_4$ | $j_1$ | $j_2$ | $j_3$ | $j_4$ | $j_1$ | $j_2$ | $j_3$ | $j_4$ |
| $i_1$ | 0 | 2V | 1B | 0 | 0 | 2V | 0 | 1B | 0 | 0 | 1B | 1B |
| $i_2$ | 0 | 2V | 0 | 0 | 2V | 0 | 0 | 0 | 2V | 0 | 0 | 0 |
| $i_3$ | 1B | 1B | 2V | 1B | 1B | 1B | 2V | 1B | 1B | 1B | 2V | 1B |
| $i_4$ | 1V | 0 | 0 | 0 | 0 | 0 | 1B | 0 | 0 | 0 | 1B | 0 |
| $i_5$ | 1V | 0 | 0 | 1B | 2V | 0 | 0 | 2V | 0 | 0 | 2V | 1B |
| $i_6$ | 2B | 0 | 4B | 2B<br>1V | 3B | 0 | 1B | 4B<br>1V | 2B | 0 | 4B | 1B<br>1V |
| | Number of vehicle trips | | | | Number of vehicle trips | | | | Number of vehicle trips | | | |
| | $j_1$ | $j_2$ | $j_3$ | $j_4$ | $j_1$ | $j_2$ | $j_3$ | $j_4$ | $j_1$ | $j_2$ | $j_3$ | $j_4$ |
| $i_1$ | 0 | 10 | 2 | 0 | 0 | 10 | 0 | 2 | 0 | 0 | 3 | 2 |
| $i_2$ | 0 | 4 | 0 | 0 | 2 | 0 | 0 | 0 | 4 | 0 | 0 | 0 |
| $i_3$ | 3 | 3 | 10 | 3 | 3 | 3 | 10 | 3 | 3 | 3 | 10 | 3 |
| $i_4$ | 10 | 0 | 0 | 0 | 0 | 0 | 3 | 0 | 0 | 0 | 3 | 0 |
| $i_5$ | 6 | 0 | 0 | 1 | 10 | 0 | 0 | 4 | 0 | 0 | 6 | 2 |
| $i_6$ | 2 | 0 | 4 | 2B<br>5V | 3 | 0 | 1 | 1B<br>10V | 2 | 0 | 4 | 1B<br>3V |

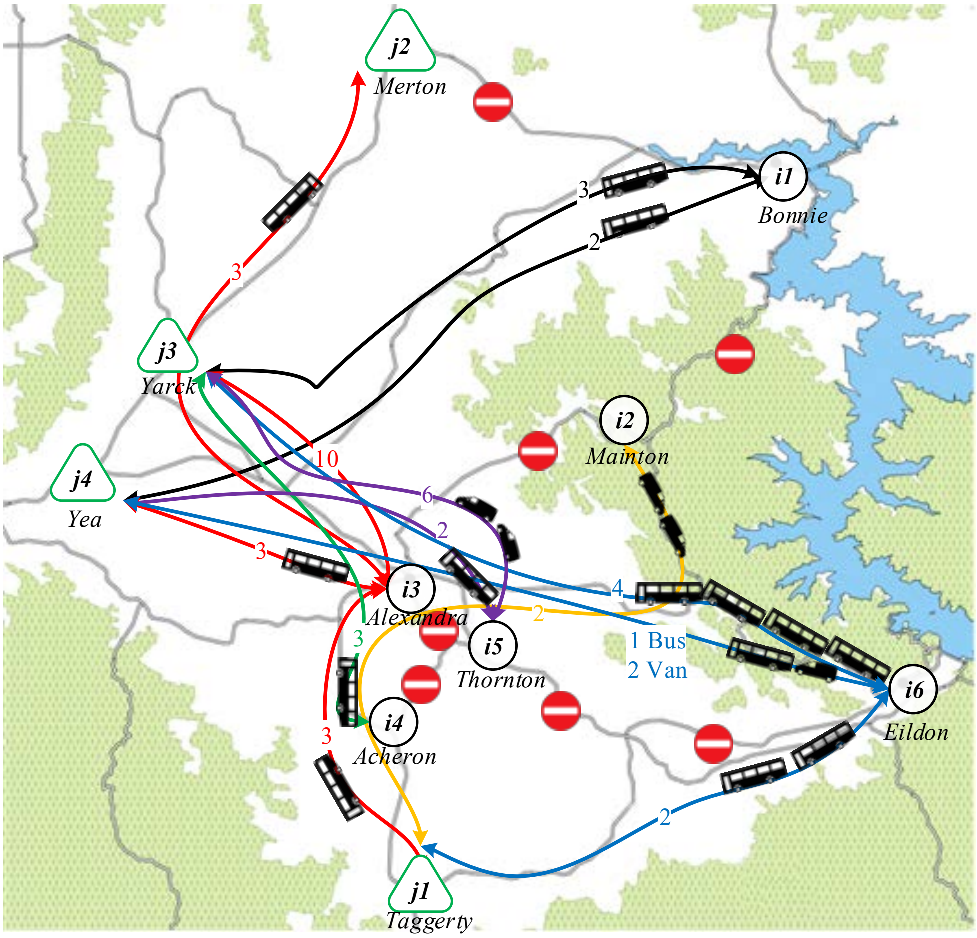
Finally, due to limitations in the number of available resources and route disruptions, combination of 4 buses and 1 van are assigned to evacuate the remaining 100 evacuees to Yea ($j_4$). In the same way for Eildon in scenario C and due to severe road disruptions and longer traversal times to reach the accessible shelters, the optimal vehicle assignment is to transfer the population by 6 buses and 1 van towards the defined shelters. Thornton ($i_5$) evacuees must be evacuated within 75 minutes to the safest and closest shelters. In scenario 1, this process is planned to be fulfilled by designation of one van doing 6 trips transferring 52 evacuees to shelter ($j_1$) plus 1 bus transferring 69 people to shelter ($j_4$) with 2 trips. While in scenario 2, the optimal vehicles assignment is to consider 2 vans traveling 10 times between $i_5$ and $j_1$ and 2 vans travelling 4 times between $i_5$ and $j_4$. Interestingly, in scenario C, all evacuees are evacuated to shelter $j_3$ and $j_4$ by application of 2 vans travelling 6 times and 1 bus travelling twice to optimise the number of the utilised vehicles within the limited time windows. The results indicate that Mainton evacuees have more time and are evacuated by assigning fewer vehicles that travel more. Figure 6.3 illustrates a better representation for the optimal emergency evacuation vehicle assignment and number of trips in each scenario.




**Bushfire Scenario 1**




**Bushfire Scenario 2**




**Bushfire Scenario 3**

Figure 6.3 Number of vehicles and trips for evacuation from the affected areas to shelters in three bushfire scenarios.

*Objective Function (Number of evacuated people):*

As shown in Table **Error! Reference source not found.**6.5 and based on the predefined bushfire scenarios, all evacuees could safely be transferred to the safe shelters. Solving the model in the first step, results in a measure of 88.8 for the objective function in scenario 1. In scenario 2, the first objective function value equals to 91.7 while due to bushfire conditions, the objective function value in scenario 3 is increased to 95.8. The increase in the preliminary objective values is caused by decreasing the transportation network size aftermath of bushfire propagation. In all of the scenarios, however, the final objective value is 1036 and indicates that all the 1036 late evacuees in hazardous townships are safely routed and sheltered by optimal assignment of the available resources.

*Number of Required Vehicles:*

The results of the first step solution of 'scenario 1' indicates that a minimum of 13 buses and 10 vans are required to transfer the entire evacuee population. However, the proposed figures are not necessarily optimal. Hence, in the second step and by application of the Ɛ-constraint method, the number of required vans decreases to 9 vans to optimise the number of available resources (Table 6.5). In the same way in scenario 2 and 3, the total numbers of assigned vehicles are optimised. For example, the total optimal number of required buses in 'scenario 2' is 13 buses while there is an increase in number of vans to mitigate the impact of extra road disruptions and cover the evacuation demands. Accordingly, in scenario 2, more vehicles are assigned to speed up the evacuation process.

Despite Eildon ($i_6$) being ranked as the second township in terms of the number of evacuees, the highest number of vehicles in all scenarios are assigned to Eildon ($i_6$) to evacuate people because of its short time window and because of the long distance to the nearest accessible shelters. Therefore, the model has assigned more vehicles to accelerate the evacuation process in Eildon.

Table 6.5 Objective functions results of three validation scenarios

| | **Bushfire scenario 1** | **Bushfire scenario 2** | **Bushfire scenario 3** |
|---|---|---|---|
| First Step Objective Value | 88.8 | 91.7 | 95.8 |
| First Step | 13 Bus, 10 Van | 14 Bus, 10 Van | 15 Bus, 12 Van |
| Objective Value (Evacuated People) | 1036 | 1036 | 1036 |
| Uncovered People | 0 | 0 | 0 |
| Number of Required Vehicles | 13 Bus, 9 Van | 13 Bus, 11 Van | 14 Bus, 7 Van |

#### 6.2.1.4 Sensitivity analysis

*Number of required shelters:*

Figure 6.4 provides the results of sensitivity analysis. Therefore, different values of available shelters are considered to determine how it can impact the total number of evacuated people under each scenario. Results indicate that due to pre-determined evacuation time windows, road blockages, distances and capacities, at least 4 shelters are required to be assigned to evacuate all evacuees in all scenarios. Obviously, assigning more shelters increases the total objective function value.

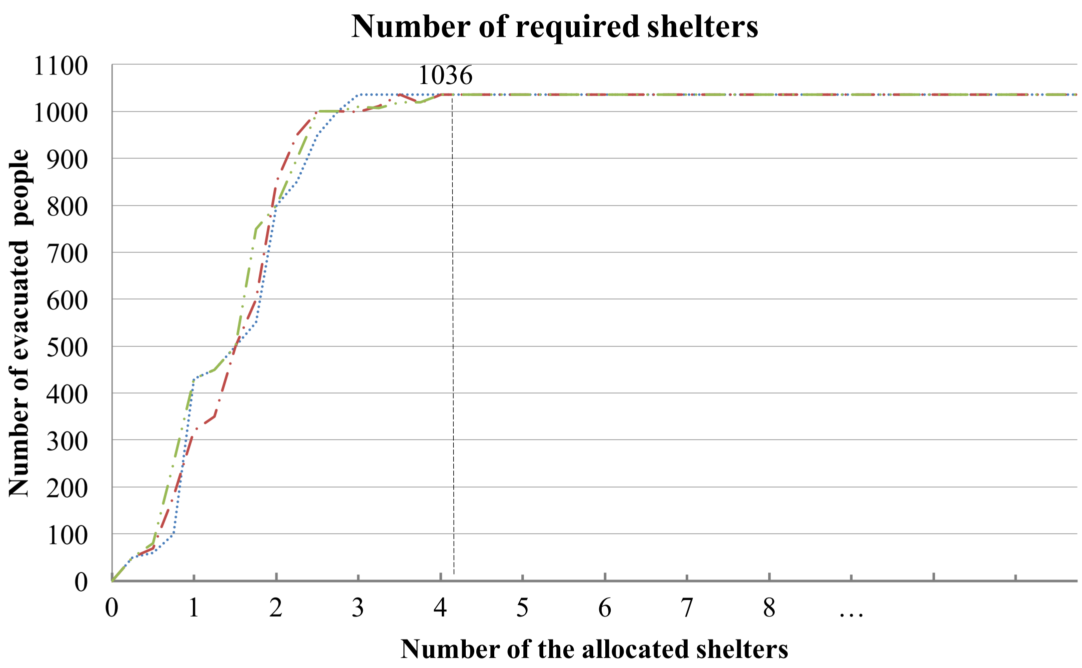
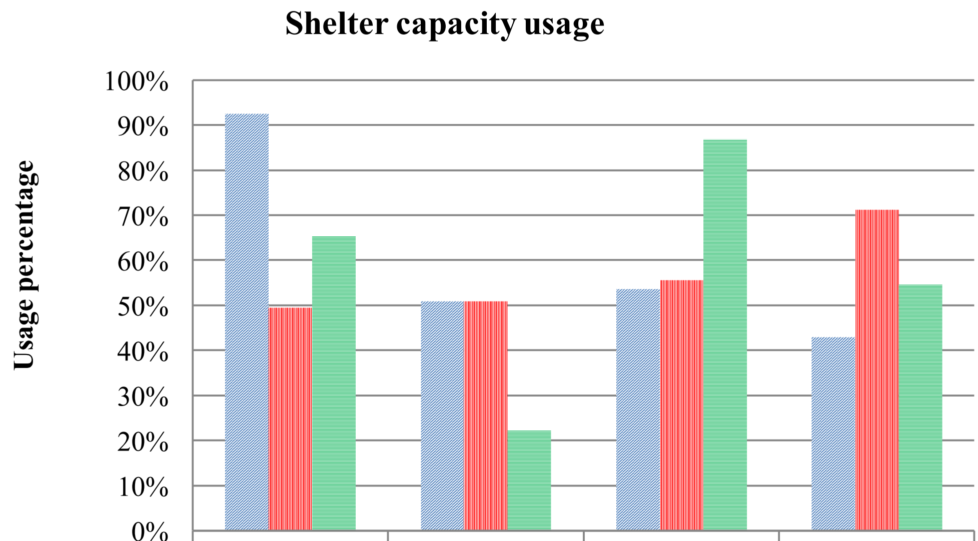



Figure 6.4 Number of required shelters (Scenario 1: blue, Scenario 2: red, and scenario 3 green).

Figure 6.5 shows the percentage of usage capacity of the designated shelters for each scenario. In scenario 1, due to the close distance to the townships, most evacuees are sheltered at Taggerty ($j_1$). However, considering the increase in number of road disruptions in scenario 2, the usage percentage of this shelter has decreased to 49.43 per cent and evacuees are transferred to other shelters. Finally, in the scenario 3, most evacuees are evacuated to Yarck ($j_3$). The capacity usage of other shelters is shown in the Figure 6.5.



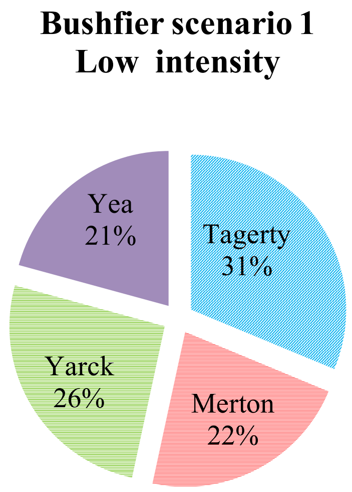

| | Taggerty | Merton | Yarck | Yea |
|---|---|---|---|---|
| Bushfire scenario 1 Low intensity | 92.57% | 50.89% | 53.60% | 43.00% |
| Bushfire scenario 2 Medium intensity | 49.43% | 50.89% | 55.60% | 71.20% |
| Bushfire scenario 3 High intensity | 65.43% | 22.22% | 86.80% | 54.60% |

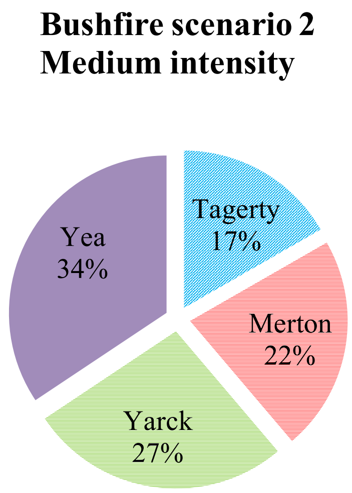
Figure 6.5 Shelters capacity usage

*Distribution of evacuees to assigned shelters*

In scenario A, people are relocated to the assigned shelters normally, however, due to the distance, limited time windows of the townships and the Northern-Mainton road disruption, most evacuees (3 per cent) are evacuated to Taggerty ($j_1$). In scenario 2, the Goulburn Valley highway disruption has impacted the transportation distribution and 353 people (34 per cent) are planned to be transferred to Yea ($j_4$) to maximise evacuated people in evacuation process (see Figure 6.6).

Finally, in scenario C, severe bushfire conditions have heavily disrupted the transportation network. Beside disruptions in the two arterial highways (Maroondah and Goulburn Valley), the Taggerty-Thornton road is the only direct linkage to Taggerty ($j_1$), which is disrupted. Consequently, most late evacuees (42 per cent) are evacuated to Yarck ($j_3$) instead of Yea ($j_4$). Nevertheless, because of limited capacity at Yarck ($j_3$) the rest of evacuees needed to be transported to the closest available shelters such as at Yea ($j_4$) and Taggerty ($j_1$). Due to Maroondah Highway blockage and the shortage of time, only 10 per cent of population could be evacuated to Merton ($j_2$).



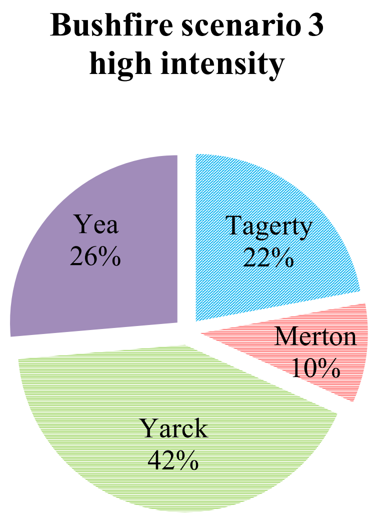




Figure 6.6 Distribution percentage of evacuees to the assigned shelters

# Application on the real case study: (Marysville bushfire)

## 6.2.2 Scenario I: Baseline

*Sensitivity analysis of optimal evacuation plans by number of functioning shelters*

There is no report that indicates an inadequate number of vehicles being available *n* the region on Black Saturday in 2009. It is therefore assumed that the maximum number of available evacuation (rescue) vehicles, $TV_V$, is $TV_{Bus}=20$ and $TV_{Van}=15$.

Furthermore, based on Black Saturday historical data, in this case study the total number of candidate shelters is five ($\Omega = 5$). However as mentioned earlier, determining the optimal allocation of reliable shelters significantly influences the evacuation routing arrangement pattern. Hence, a sensitivity analysis of the optimal evacuation plans (e.g. optimal transportation, routing and trips) in relation to the maximum number of available shelters $\Omega$ is provided in Table A3, in the Appendix.

As shown in Table A3 in the Appendix, the optimal number of shelters is four ($\Omega = 4$), where five buses and twelve vans are used. Figure 6.5 illustrates the optimal deployments and the evacuee-to-shelter allocation results, with functioning shelters indicated by green triangles on the map. Each assigned vehicle follows its route, and the number of required trips is listed above each vehicle. Secondary routes are highlighted via dashed lines.

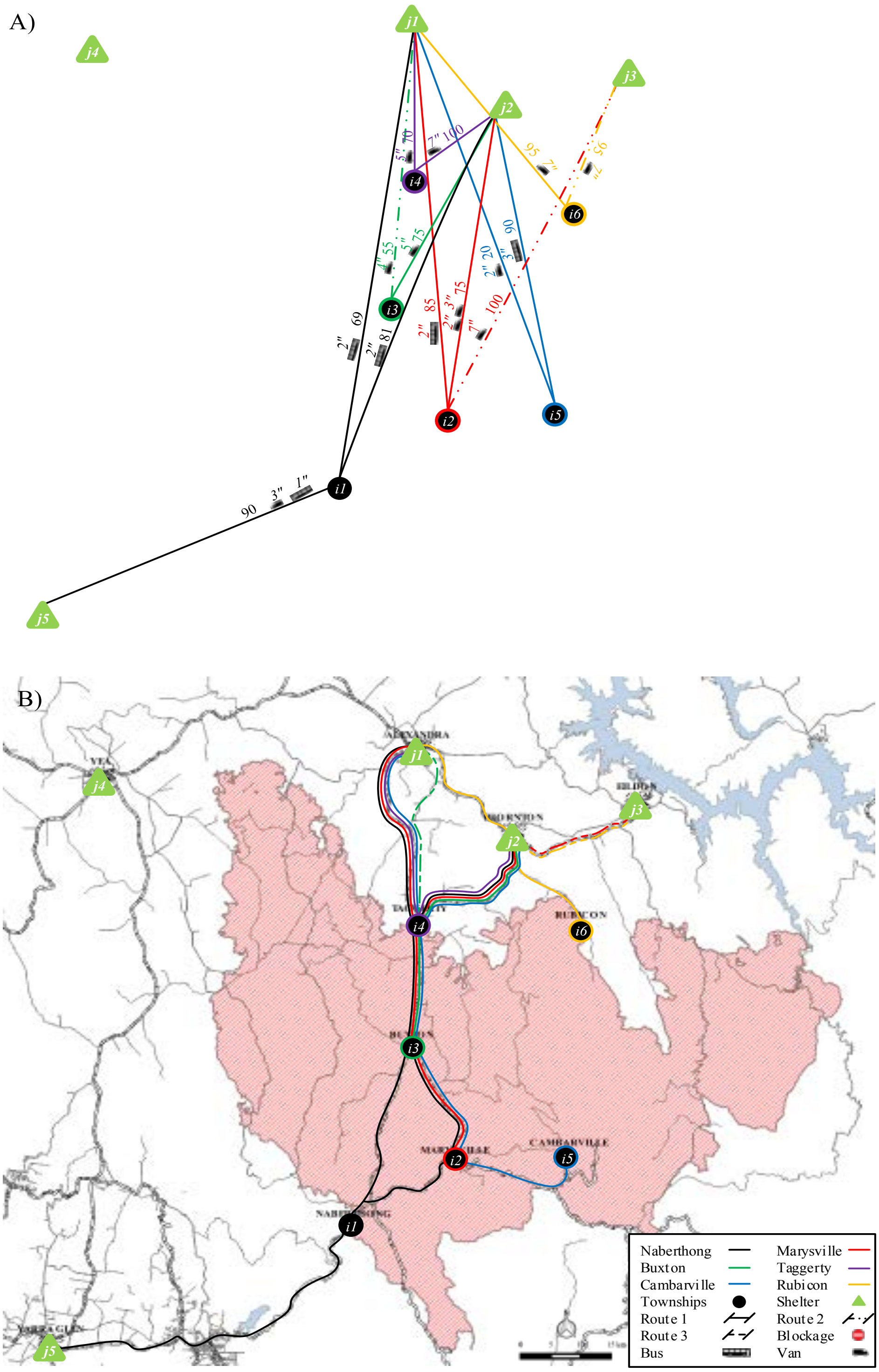



Figure 6.7 Optimal routing evacuation plan via the assignment of four functioning shelters, five buses and twelve vans.

In the Figure 6.7, the evacuation routes for each township are depicted by different colours. A solid line indicates that "route 1" is chosen for the transportation of evacuees, while the dashed line is used as a symbol of "route 2". In the left figure, the numbers above each assigned vehicle (a bus or van) shows the number of trips required to evacuate the entire assigned evacuee population to each of shelters shown in front of vehicles. The right figure illustrates the evacuation plan in its real context.

The results show that the high-capacity shelters have been used most frequently to centralise the routing plan distribution. In addition, it is observed that heavily-populated areas tend to be evacuated to denser shelters (for example, Marysville $(i_2)$ is mostly evacuated to Alexandra $(j_1)$ and Thornton $(j_2)$). Accordingly, the dispersion of vehicle trip patterns is more centralised (routing via single route alternatives), as the number of shelters decreases. Contrary to the expected insights, it is interesting to note that increasing the number of shelters does not drastically increase vehicle assignment. It indicates that for as long as possible, the model resists the spread disruption of evacuees by increasing the number of shelters (which, of course, increases the expected number of required travels) (Figure 6.8). Different line colours are utilised for paths to show the evacuation paths of each township. In each scenario, the evacuation process is limited to the number of available functioning shelters as indicated in the pattern above each.

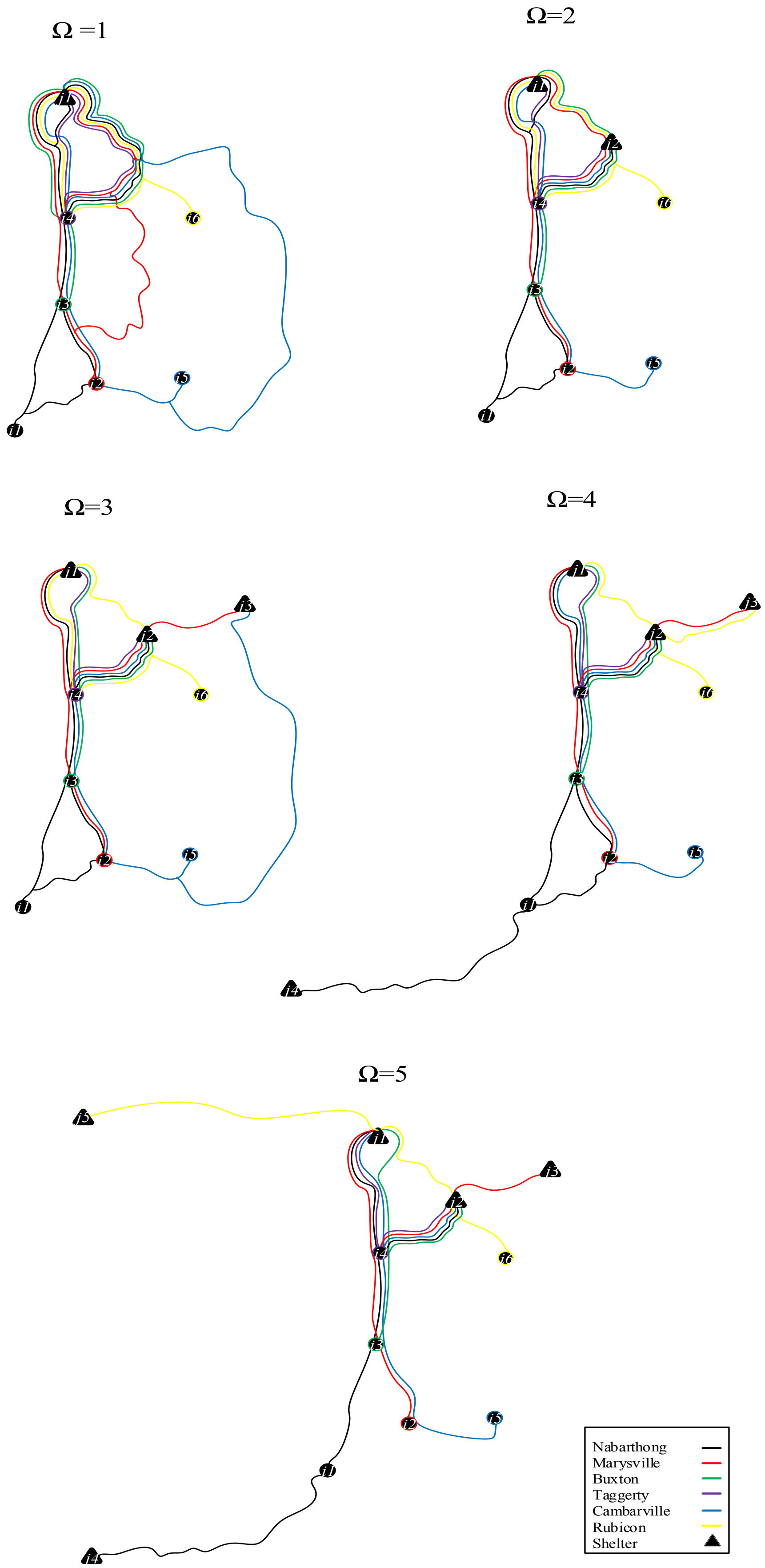



Figure 6.8 Optimal routing pattern by different number of functioning shelters.

It is noted that for as long as possible, the model tends to decrease the number of assigned vehicles according to the sufficiency of time to travel (which, of course decreases the objective function). For example, in the case that $\Omega = 4$, Rubicon late evacuees are planned to be moved by only one van travelling seven times between Rubicon and Eildon, due to sufficient time being available.

The results also show that as the number of available shelters $(\Omega)$ increases, the number of rescue vehicles tends to increase slightly (i.e. when $\Omega =$2, 3, 4, and 5, the respective number of assigned vehicles are 6 buses-13 vans, 7 buses-11 vans, 5 buses-12 vans, and 6 buses-12 vans). However, with $\Omega = 1$, more available vehicles (10 buses - 11 vans) are used to reduce the risk of disruptions for longer trips from more distant townships. Interestingly, in this case, in order to avoid traffic congestion and reduce the rescue fleet traversal speed, vehicles are distributed across most alternative routes in the network. Using this approach, all evacuees could be transported before the bushfire disruptions. In addition, shelters further away are backed up by those closer, to be utilised only in the case of contingent functioning failures of closer shelters (e.g., the Yea shelter is not allocated in cases where $\Omega \leq 4$). In reality, a fewer number of shelters is more manageable. However, in the event of a severe bushfire, contingent outbreak failures and disruptions in resources and infrastructures may exacerbate the evacuation mission. Therefore, such a strategy may not be appropriate. This finding highlights the need to consider backup shelters in emergency evacuation planning.

This finding also highlights the need for a rigorous system-level approach to transit-based evacuation system planning, rather than relying on intuition. Furthermore, to investigate the impact of vehicles on the optimal number of required shelters, another sensitivity analysis has been conducted. For simplicity and illustration, it is assumed that only buses are used. The results show that the optimal number of required vehicles initially increased in different scenarios (changing the number of $\Omega$), then subsequently became independent. While utilising fourteen buses, the optimal number of required shelters remained as four, however the objective function increased to 73.9. In addition, as illustrated in Figure 6.9, any further increase in the number of buses has not affected the evacuation plan of the entire impacted network.

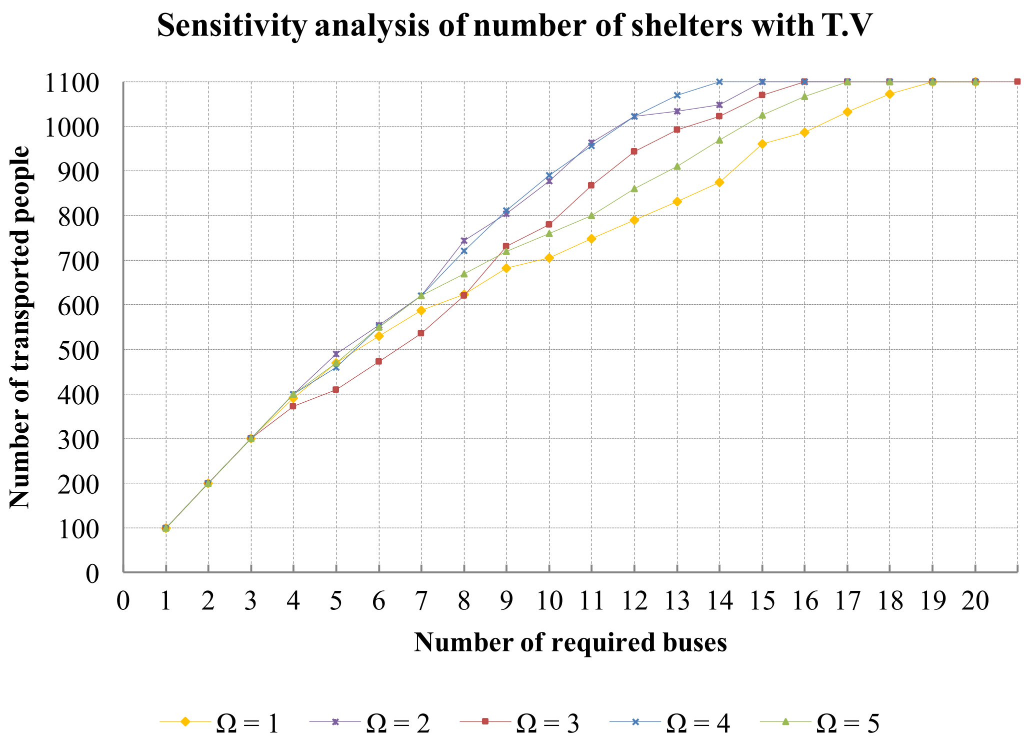



Figure 6.9 Sensitivity analysis of the number of functioning shelters with the total number of buses.

Sensitivity analysis with respect to the time impedance was also carried out on the optimal evacuation plan to investigate the effect of traffic on the evacuation plan. The results show that the minimum number of required vehicles to evacuate all evacuees increases by time impedance factor. In case that there is no traffic in the network (T=0), a minimum of 13 buses can evacuate all evacuees while by T = 80 per cent at least 17 buses are required to cover all evacuees (Figure 6.10) Different colours are used to depict the related graphs based on time impedance factors.

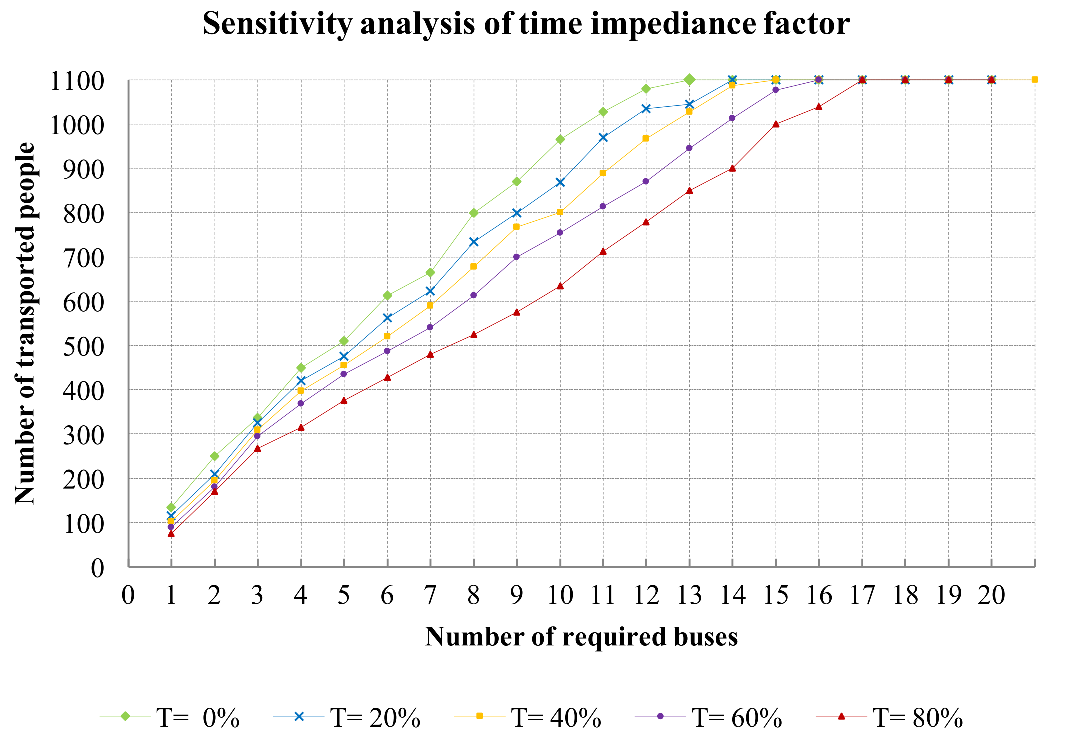



Figure 6.10 Sensitivity analysis of the time impedance factor with the total number of buses.

To show the effect of dwelling time on the overall output of the model, a sensitivity analysis was carried out based on the selection of various dwelling times (waiting/boarding/alignment). As shown in the Figure 6.11, in this case with the dwell time values around the considered average dwell time (12.5 seconds per person) there is no significant difference on the overall output. However, in some cases higher dwell time values may lead to significant delays in the evacuation process. For instance, in the worst case by considering 30 seconds per person as the dwell time, there is a significant number of buses required to cover all the evacuation demands. Different colours are used to show related dwell times.

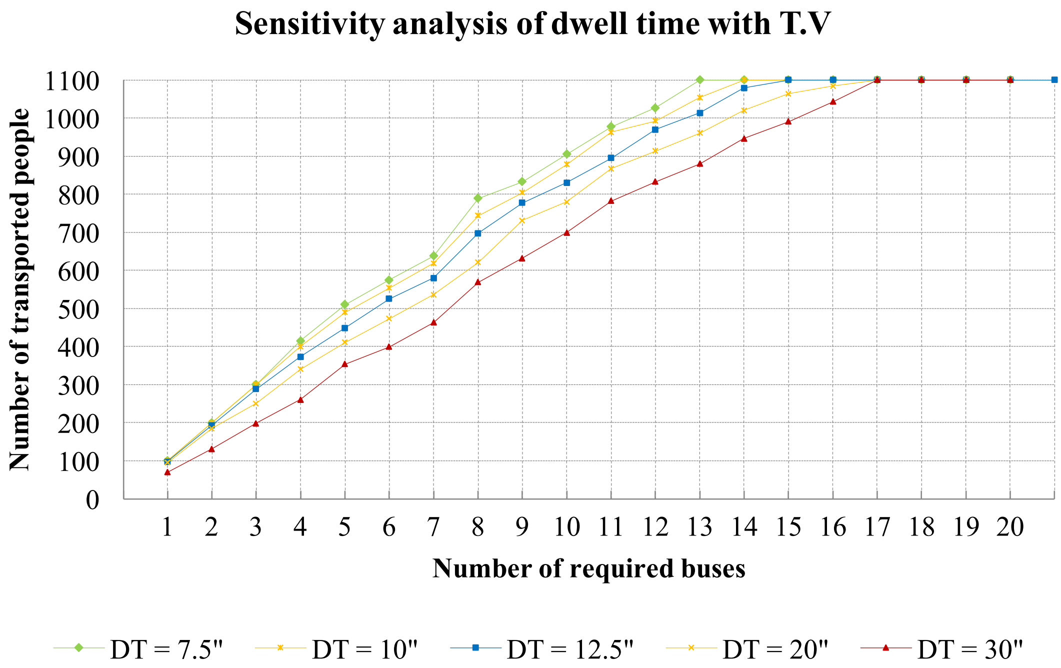



Figure 6.11 Sensitivity analysis of the dwell time factor with the total number if required buses.

In order to analyse the effect of different evacuation demands on the output plan, a sensitivity analysis was conducted with both lower and higher populations (Figure 6.12). The analysis shows that an increase in population is in direct relation to the number of required buses to evacuate all the population within the predefined time windows.

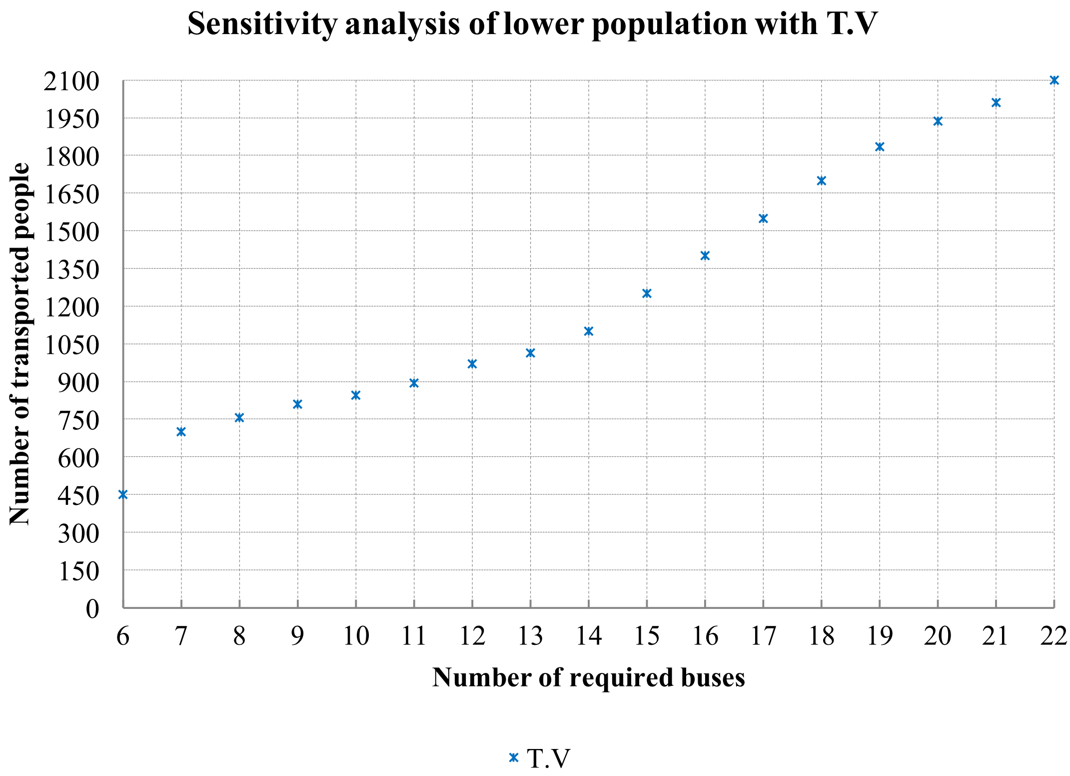



Figure 6.12 Sensitivity analysis of the dwell time factor with the total number of required buses.

### 6.2.3 Scenario II: disruption in the high capacity shelter

In a bushfire emergency evacuation, there are key parameters, such as wind direction and speed, the accessibility and availability of resources, and evacuee behavioural factors, that all may heavily impact the evacuation process. Among these parameters, abrupt variation in the availability and accessibility of resources is known to be the most significant issue that can be mitigated by applying an appropriate decision tool (Shahparvari et al., 2016a, Shahparvari et al., 2015d). Hence, the two following scenarios are designed to evaluate the reliability of the model in generating an optimal evacuation plan in the case of unforeseen road disruptions and shelter availability.

In this case study, most late evacuees had been evacuated to Alexandra. However, due to bushfire spread direction and acceleration, emergency services were uncertain of the availability/accessibility of the Alexandra township. Given that shelter in the Alexandra township plays such a key role in serving evacuees, it was interesting to test the model for the eventuality that the model was tested with the assumption of unavailability of

Alexandra. Figure 6.13 shows the percentages of usage capacity of the designated shelters for each such case.

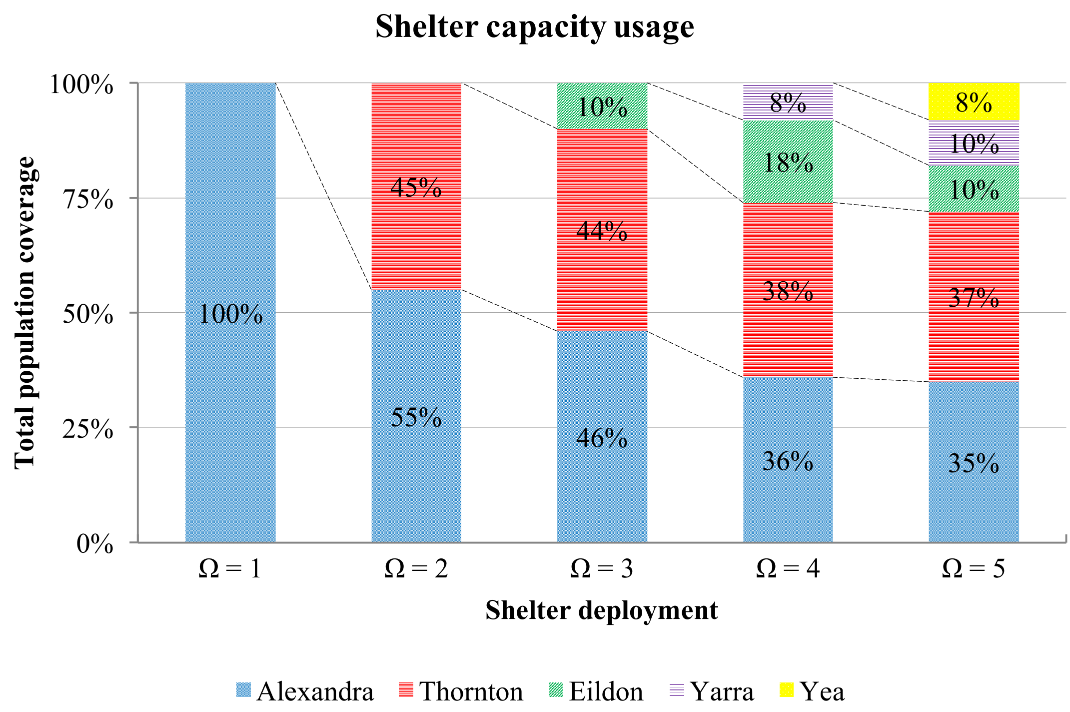



Figure 6.13 The result of shelter capacity usage dispersion.

In Figure 6.13, the y-axis denotes the total evacuee population covered by the utilisation of different numbers of available shelters in different scenarios (x-axis). The usage capacity of each shelter under each scenario is indicated on the related bar graph and plotted in a different colour.

In this case the other four shelters are assumed to remain available. The optimal plan to save all of evacuees within the rigid time windows is to route late evacuees to the three shelters in Thornton $(j_2)$, Eildon $(j_3)$and Yarra $(j_4)$, as prescribed in Table 6.6.

Table 6.6 Optimal evacuation plan when Alexandra ( $j_1$) is unavailable

| | | | | Evacuees routing plan | | | Number of required vehicles | | | | Number of trips | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Number of available shelters | Optimal assignment of the resources | From | To | Route 1 | Route 2 | Route 3 | Vehicle | Route 1 | Route 2 | Route 3 | Route 1 | Route 2 | Route 3 |
| $\Omega = 4$ | Assigned shelters<br>-Thornton<br>-Eildon<br>-Yarra<br>Number of vehicles<br>-Bus 6<br>-Van 12<br><br>Objective function value<br>56.85 | Narbethong | Thornton | 80 | 60 | - | Bus | 1 | 1 | - | 2 | 2 | - |
| | | | Yarra | 100 | - | - | Bus | 1 | - | - | 1 | - | - |
| | | | | | | | Van | 2 | - | - | 3 | - | - |
| | | Marysville | Thornton | 75 | - | - | Van | 2 | - | - | 5 | - | - |
| | | | Eildon | 85 | 100 | - | Bus | 1 | - | - | 2 | - | - |
| | | | | | | | Van | - | 2 | - | - | 7 | - |
| | | Buxton | Thornton | 85 | - | - | Van | 1 | - | - | 6 | - | - |
| | | | Eildon | 45 | - | - | Van | 1 | - | - | 3 | - | - |
| | | Taggerty | Thornton | 100 | - | - | Van | 1 | - | - | 7 | - | - |
| | | | Eildon | - | 70 | - | Van | - | 1 | - | - | 5 | - |
| | | Cambarville | Eildon | 65 | 45 | - | Bus | 1 | 1 | - | 2 | 1 | - |
| | | Rubicon | Thornton | 100 | - | - | Van | 1 | - | - | 7 | - | - |
| | | | Eildon | - | 90 | - | Van | - | 1 | - | - | 6 | - |

Table 6.6 demonstrates that, due to the unavailability of the Alexandra $(j_1)$ shelter, the objective function is increased by 7 per cent. This result highlights that the assignment of fewer shelters does not inevitably decrease the total cost function, although it may slightly increase the number of used vehicles. The illustration of the evacuation disruption in Figure 6.14 demonstrates that the unavailability of Alexandra has not significantly impacted the optimal routing pattern.

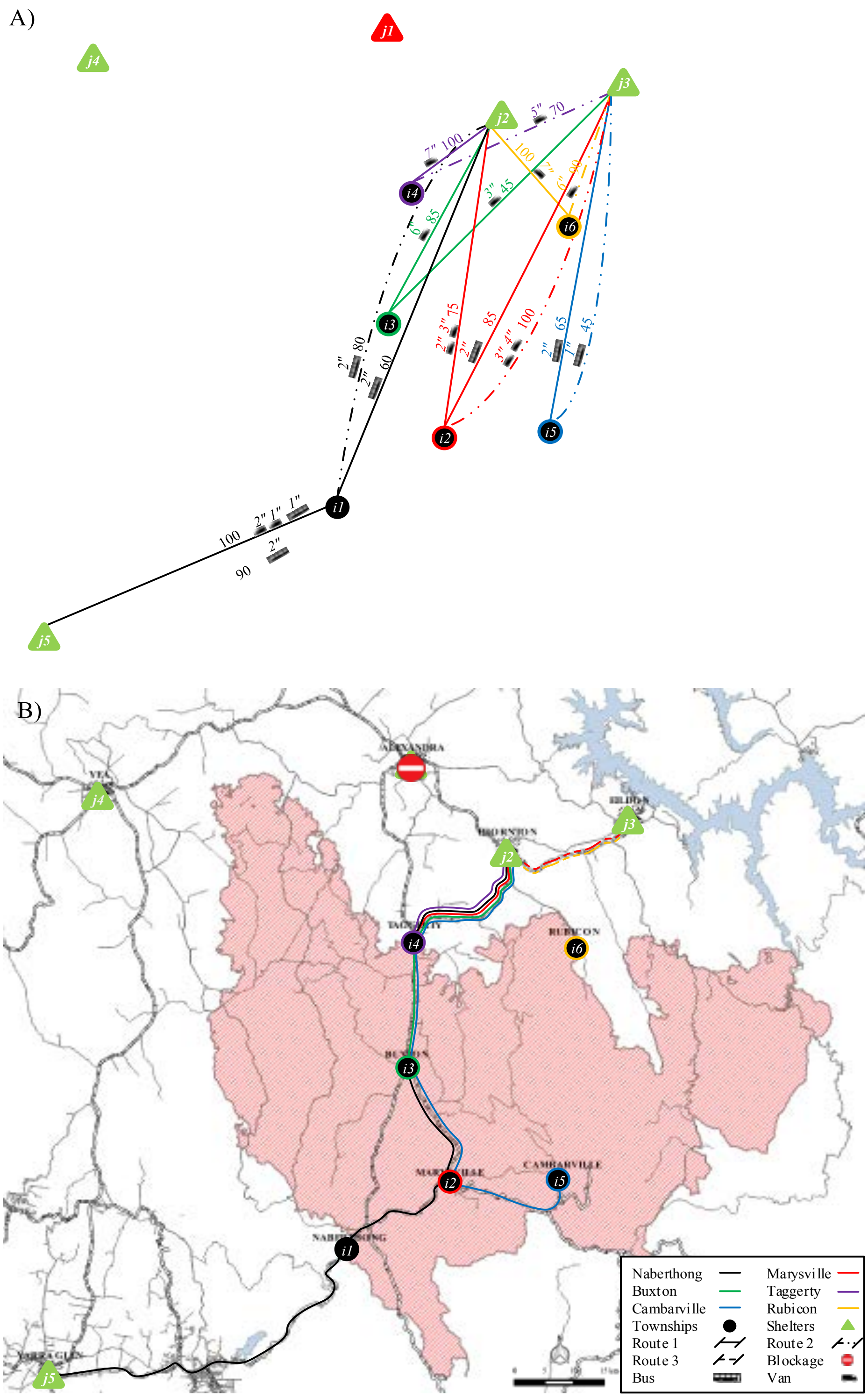



Figure 6.14 Optimal evacuation plan under a central shelter disruption.

In the Figure 6.14, the evacuation routes for each township are depicted by different colours. A solid line indicates that “route 1” is chosen for the transportation of evacuees, while the dashed line is used as symbol of the “route 2”. In the upper figure, the numbers above each assigned vehicle (bus or van) shows the number of required trips to evacuate the entire assigned evacuee population to each path shown in front of each vehicle. The lower figure illustrates the evacuation plan in its real context.

### 6.2.4 Scenario III: disruption to both highly used roads and shelters

It is vital to evaluate how the third model reacts against different levels of road accessibility. The results show that more than half of evacuees (59 per cent) could be evacuated to the designated shelters in the northern parts of the region via the Maroondah Highway (B360 that is coded as link $l_{17}$ in Figure 3.5). The Maroondah Highway and its related road links thus play a critical role in the evacuation. Let us assume that Maroondah Highway is no longer accessible. Given $\Omega = 4$, and infinite vehicles in order to consider the extreme case. In contrast with what is expected, the result shows that the optimal result is to use three out of four functional shelters, as shown in Table 6.7.

Table 6.7 Optimal routing plan under intense disruption

| | | | | Evacuees routing plan | | | Number of required vehicles | | | | Number of trips | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Number of available shelters | Optimal assignment of the resources | From | To | Route 1 | Route 2 | Route 3 | Vehicle | Route 1 | Route 2 | Route 3 | Route 1 | Route 2 | Route 3 |
| $\Omega = 4$ | Assigned shelters | Narbethong | Eildon | - | - | 45 | Bus | - | - | 1 | - | - | 1 |
| | -Alexandra | | Yarra | 105 | 90 | - | Bus | 1 | 1 | - | 2 | 2 | - |
| | -Eildon | | | | | | Van | 1 | - | - | 1 | - | - |
| | -Yarra | Marysville | Alexandra | - | - | 70 | Bus | - | - | 1 | - | - | 1 |
| | Number of vehicles | | | | | | Van | - | - | 2 | - | - | 1 |
| | -Bus 14 | | Eildon | - | 90 | - | Bus | - | 2 | - | - | 1 | - |
| | -Van 10 | | Yarra | 100 | - | - | Bus | 2 | - | - | 1 | - | - |
| | | | | | | | Van | 1 | - | - | 1 | - | - |
| | Objective function value 92.85 | Buxton | Alexandra | - | - | 40 | Bus | - | - | 1 | - | - | 1 |
| | | | Yarra | 90 | - | - | Bus | 2 | - | - | 1 | - | - |
| | | Taggerty | Alexandra | - | 100 | 70 | Van | - | 1 | 1 | - | 7 | 5 |
| | | Cambarville | Alexandra | - | - | 10 | Van | - | - | 1 | - | - | 1 |
| | | | Eildon | - | 100 | - | Bus | - | 2 | - | - | 1 | - |
| | | | | | | | Van | - | 1 | - | 1 | - | - |
| | | Rubicon | Alexandra | 40 | 60 | - | Van | 1 | 1 | - | 3 | 4 | - |
| | | | Eildon | 90 | - | - | Bus | 1 | - | - | 2 | - | - |

In addition, the objective function increases due to an increase in the number of allocated vehicles (14 buses-10 vans). This may be partially due to the longer routes.

Therefore, this indicates that neglecting the vulnerability of contingent risks (e.g. a collision, or network disruption), which are prevalent in most of the past incidents, may provide sub-optimal allocation solutions. Figure 6.15 shows how the evacuee dispersion and routing change with varying degree of disruptions.

Figure 6.15 shows the results of the scenario where the main road is disrupted by bushfire. It demonstrates that the denser and higher capacity shelters (in this case Alexandra and Eildon) can accommodate more evacuees, while demanding more emergency vehicles.

The results of the modelling indicate the importance of real-time information about shelters and route disruptions, which has the potential to influence the optimised solution. A number of available shelters should be allocated adjacent to the central bushfire-prone shelters, while the more bushfire-prone shelters can be allocated closer to the impacted region's boundaries. The model tends to allocate shelters in areas of high demand. In addition, the allocated shelters are likely to support each other when unforeseen failures occur in the coordination of emergency evacuation.

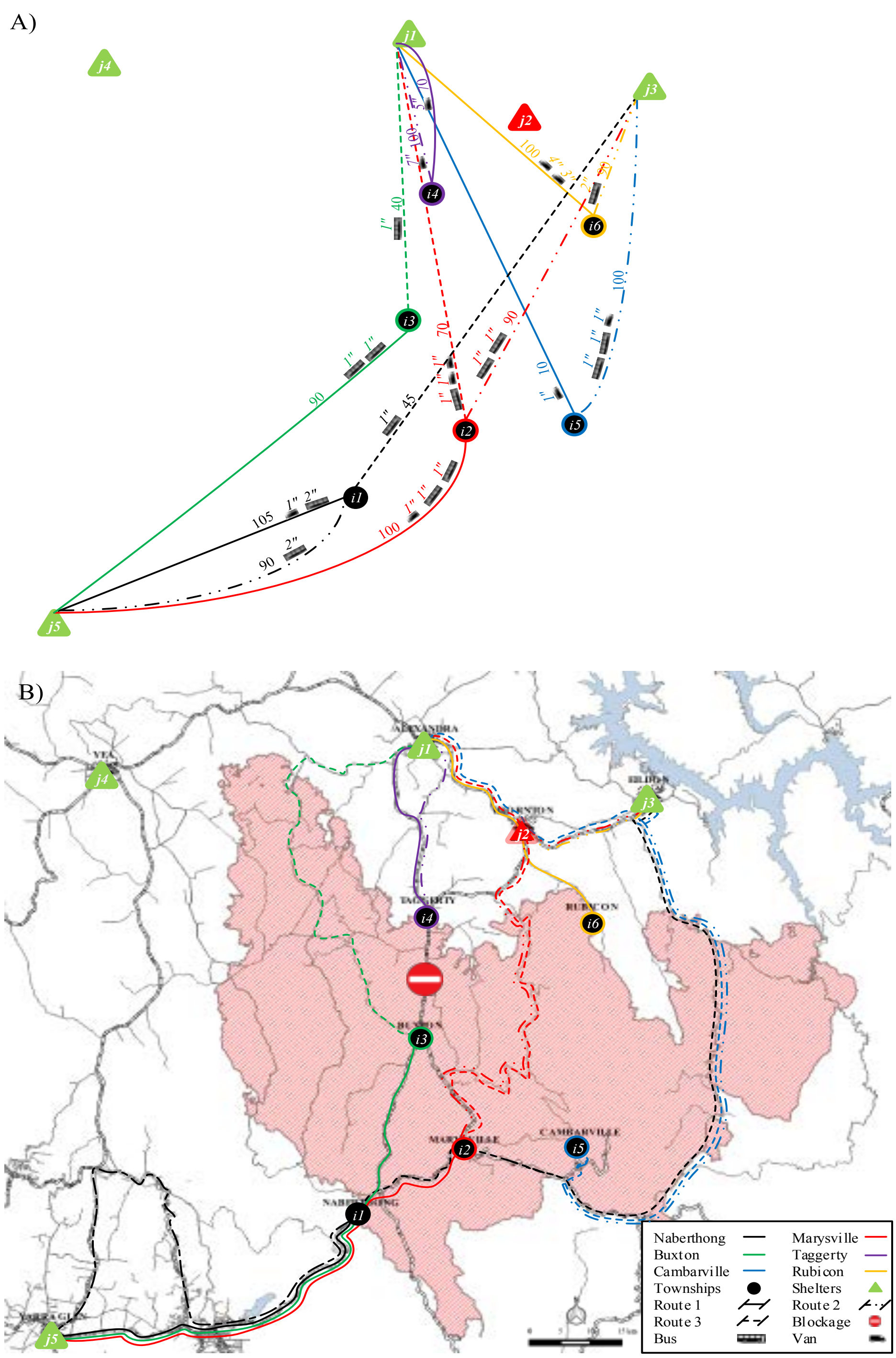



Figure 6.15 Optimal evacuation plan under both road and shelter disruptions.

In Figure 6.15, It is assumed that the main road segment is disrupted and no longer accessible as well as the Thornton township ($j_2$). In the figures, the evacuation routes for each township are depicted by different colours. A solid line indicates that "route 1" is chosen for the transportation of evacuees, while the dashed line is used as symbol of the alternative "route 2". In the upper figure, the numbers above each assigned vehicle (bus or van) show the number of required trips to evacuate the entire assigned evacuee population to each path shown in front of each vehicle. The lower figure illustrates the evacuation plan in its real context.

## 6.3 Model II: CMDVRP-TW

### 6.3.1 Validation: application on small size case study (Lake Eildon Park)

The purpose of this section is to investigate the capability of the developed model to generate valid optimal emergency evacuation routing plans by the minimum utilisation of available resources such as vehicles and shelters. By means of this procedure, taking into account the network dynamics, vehicles can be routed in accordance with context constraints as roads availability, shelter and vehicle capacity that vary over time.

*Results of validation:*

The results indicate that the model has generated seven optimal routing plans to evacuate all the 1030 evacuees within the pre-defined evacuation time windows (Table 6.8).

Table 6.8 Optimal routing distribution plan

| **Bus1** | **Bus 2** | **Bus 3** | **Bus 4** | **Bus 5,6,7** |
|---|---|---|---|---|
| From→To | From→To | From→To | From→To | From→To |
| $i_5 \rightarrow j_1$ | $i_3 \rightarrow j_3$ | $i_3 \rightarrow j_3$ | $i_6 \rightarrow j_4$ | $i_6 \rightarrow j_4$ |
| $j_1 \rightarrow i_5$ | $j_3 \rightarrow i_3$ | $j_3 \rightarrow i_3$ | $j_4 \rightarrow i_2$ | |
| $i_5 \rightarrow j_1$ | $i_3 \rightarrow j_3$ | $i_3 \rightarrow j_3$ | $i_2 \rightarrow j_1$ | |
| $j_1 \rightarrow i_5$ | $j_3 \rightarrow i_3$ | $j_3 \rightarrow i_3$ | $j_1 \rightarrow i_1$ | |
| $i_5 \rightarrow j_1$ | $i_3 \rightarrow j_3$ | $i_3 \rightarrow j_3$ | $i_1 \rightarrow j_4$ | |
| $j_1 \rightarrow i_4$ | $j_3 \rightarrow i_3$ | $j_3 \rightarrow i_3$ | | |
| $i_4 \rightarrow j_1$ | $i_3 \rightarrow j_3$ | $i_3 \rightarrow j_3$ | | |
| $j_1 \rightarrow i_3$ | $j_3 \rightarrow i_1$ | $j_3 \rightarrow i_1$ | | |
| $i_3 \rightarrow j_1$ | $i_1 \rightarrow j_3$ | $i_1 \rightarrow j_3$ | | |
| $j_1 \rightarrow i_4$ | | | | |
| $i_4 \rightarrow j_1$ | | | | |
| $j_1 \rightarrow i_1$ | | | | |
| $i_1 \rightarrow j_3$ | | | | |
| Evacuated 315 | 225 | 225 | 135 | 45 × 3 |
| Total Transferred | | 1030 | | |

Table 6.8 shows, that to maximise the total evacuated people at the first run, the first

vehicle's service is planned to start from Thornton ($i_5$) which has a 75 minutes time window to evacuate 121 people. Therefore, in the first time period (*k*=1, 45 mins) bus number 1 travels twice between Thornton ($i_5$) and Taggerty ($j_1$) as the closest available shelter and transfers 90 evacuees. At the end of first time period (45 mins) the first bus is at Thornton ($i_5$), whereas there is still enough time (30 minutes) to return to Taggerty ($j_1$). Then at the start of the second time period (*k=2,)* the first bus has travelled to ($j_1$) again and transferred 45 more people (Figure 6.16).

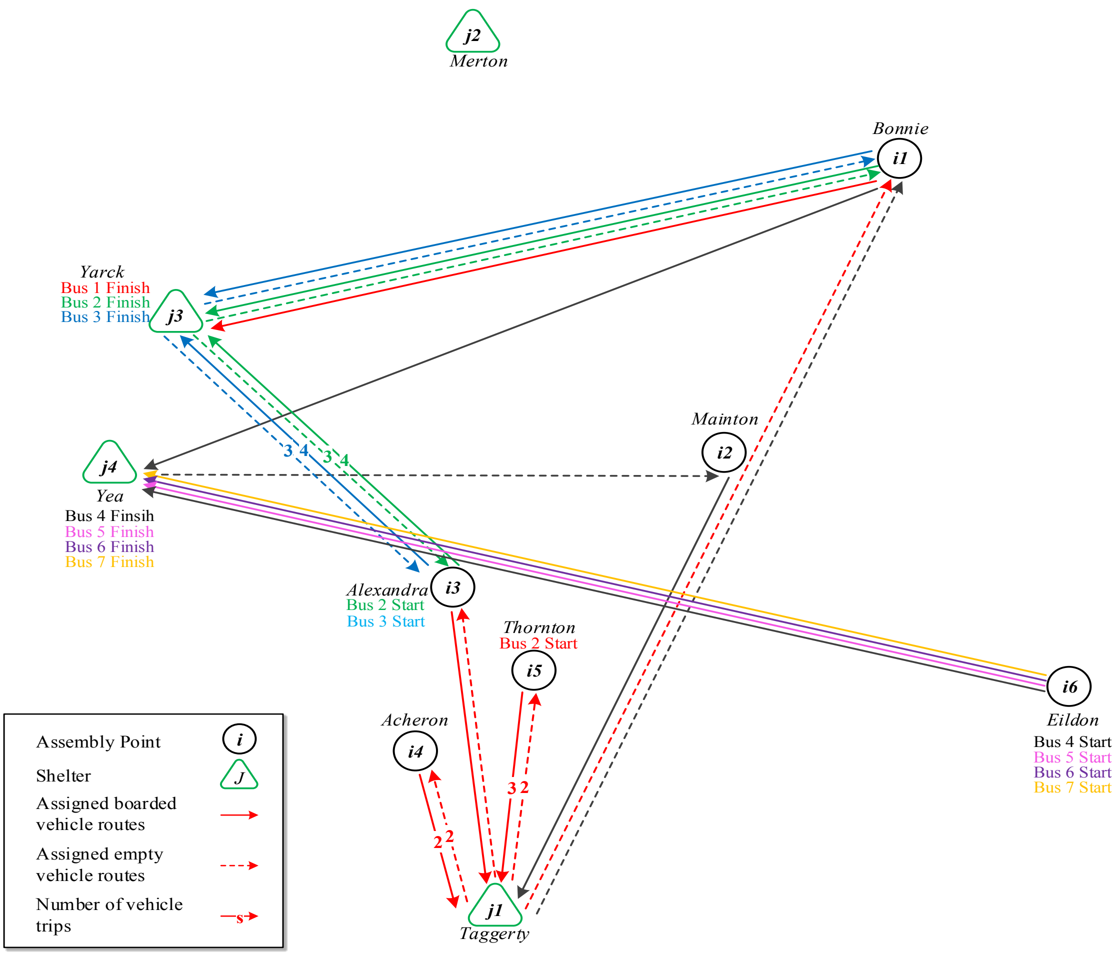



Figure 6.16 Routing map for evacuation of people in the Lake Eildon national park area

At this time all the Thornton population are evacuated to Yarck before its time window is finished (*k*=2, 75 mins). At this moment, the first bus is assigned to serve the evacuation operation by traveling to the next closest township as Acheron ($i_4$). At (*k*=3) the bus has reached Acheron. It has boarded evacuees and returned to Taggerty ($j_1$). In the same way, as it has been shown in Table 6.8, the first bus continues routing between the townships and evacuates the late evacuees until the time windows are over.

### 6.3.2 Scenario I: Baseline

The main aim of this Section is to demonstrate how the proposed model can be utilised to enhance the emergency evacuation planning and performance process order to save more lives. Plausible scenarios from the 2009 Murrindindi Mill bushfire case study, were examined and are presented to demonstrate the problem methodology and analytical solutions. In the emergency evacuation research literature, the allocation of reliable functioning shelters under stringent constraints is frequently cited as the most important and potentially impacting element of the evacuation process (Shahparvari et al., 2016a, An et al., 2013). Therefore, sensitivity analysis via changing this key assigned shelters parameter is provided in this Section to enable insights to be drawn on how such changes affect the performance of the emergency evacuation process. In addition, shelter capacity usage in each scenario is investigated. The model was implemented using the CPLEX solver 12.6, on a PC with 3.40 GHz CPU and 8 GB RAM (CPLEX, 2005). The case study size is kept to medium in order to be solvable by commercial software and for the outcomes to be analysed and discussed more easily. However, the parameters and scenarios chosen are adequate to ensure the performance of the proposed model. It is notable that the proposed model does not have an upper limit on input parameters or the network size.

*Evacuation planning in the baseline*

Table 6.9 shows that the evacuation plan is achieved via utilising four evacuee shelters and seven buses.

Table 6.9 The evacuation plan in the baseline

| Vehicle | Time period | From | To | Route 1 | Route 2 | Route 3 | Transferred: Assembly points | Transferred: Population | Lost evacuees: Assembly points | Lost evacuees: Population |
|---|---|---|---|---|---|---|---|---|---|---|
| Bus 1 | $m_1$ | Marysville | Thornton | × | | | Marysville | 45 | Narbethong | 240 |
| | | Thornton | Buxton | × | | | Buxton | 130 | Marysville | 215 |
| | $m_2$ | Buxton | Thornton | × | | | Taggerty | 170 | Cambarville | 110 |
| | | Thornton | Buxton | × | | | Rubicon | 190 | | |
| | $m_3$ | Buxton | Thornton | × | | | | | | |
| | | Thornton | Buxton | × | | | | | | |
| | | Buxton | Thornton | × | | | | | | |
| | | Thornton | Taggerty | × | | | | | | |
| | $m_4$ | Taggerty | Thornton | × | | | | | | |
| | | Thornton | Taggerty | × | | | | | | |
| | | Taggerty | Thornton | × | | | | | | |
| | | Thornton | Taggerty | × | | | | | | |
| | | Taggerty | Thornton | × | | | | | | |
| | | Thornton | Taggerty | × | | | | | | |
| | | Taggerty | Thornton | × | | | | | | |
| | | Thornton | Rubicon | × | | | | | | |
| | $m_5$ | Rubicon | Thornton | × | | | | | | |
| | | Thornton | Rubicon | × | | | | | | |
| | $m_6$ | Rubicon | Thornton | × | | | | | | |
| | | Thornton | Rubicon | × | | | | | | |
| | | Rubicon | Thornton | × | | | | | | |
| | | Thornton | Rubicon | × | | | | | | |
| | | Rubicon | Thornton" | × | | | | | | |
| | | Thornton | Rubicon | × | | | | | | |
| | | Rubicon | Alexandra | × | | | | | | |
| Bus 2 | $m_1$ | Cambarville | Alexandra | × | | | Cambarville | 90 | Narbethong | 240 |
| | | Alexandra | Marysville | × | | | Marysville | 45 | Marysville | 170 |
| | $m_2$ | Marysville | Alexandra | × | | | | | Cambarville | 20 |
| | | Alexandra | Cambarville | × | | | | | | |
| | $m_3$ | Cambarville | Eildon | | × | | | | | |
| Bus 3 | $m_1$ | Narbethong | Yarra | × | | | Narbethong | 45 | Narbethong | 195 |
| | | Yarra | Marysville | × | | | Marysville | 45 | Marysville | 125 |
| | $m_2$ | Marysville | Alexandra | | × | | Cambarville | 20 | | |
| | | Alexandra | Cambarville | × | | | | | | |
| | $m_3$ | Cambarville | Eildon | | × | | | | | |
| Bus 4 | $m_1$ | Marysville | Alexandra | × | | | Marysville | 125 | Narbethong | 195 |
| | | Alexandra | Marysville | × | | | | | | |
| | $m_2$ | Marysville | Alexandra | × | | | | | | |
| | | Alexandra | Marysville | × | | | | | | |
| | | Marysville | Alexandra | × | | | | | | |
| Bus 5 | $m_1$ | Narbethong | Yarra | × | | | Narbethong | 90 | Narbethong | 105 |
| | | Yarra | Narbethong | × | | | | | | |
| | | Narbethong | Yarra | × | | | | | | |
| Bus 6 | $m_1$ | Narbethong | Yarra | × | | | Narbethong | 90 | Narbethong | 15 |
| | | Yarra | Narbethong | × | | | | | | |
| | | Narbethong | Yarra | × | | | | | | |
| Bus 7 | $m_1$ | Narbethong | Yarra | × | | | Narbethong | 15 | | 0 |
| Total | | | | | | | | 1100 | | |

Bus 1 for example is scheduled to start its service from Marysville $(i_2)$, transporting its first group of late evacuees via the safest route to the closest shelter at Thornton$(j_2)$. Due to the short time window and the traveling distance, Bus 1 does not have enough time to return to Marysville $(i_2)$ to evacuate more people. Therefore, Bus 1 departs from Thornton $(j_2)$ and travels instead to Buxton $(i_4)$ to continue the evacuation process from there. It is notable that after Narbethong $(i_1)$ and Marysville$(i_2)$, Buxton $(i_4)$ has the least time window for the bushfire propagation. As the results in Table 6.9

further indicate, all 130 late evacuees from Buxton ($i_4$) are evacuated via the lowest risk route one in three round trips ($m = 3$) before the bushfire reaches the town. After the last group of late evacuees at Buxton ($i_4$) arrives at Thornton ($j_2$), Bus 1 proceeds to Taggerty ($i_3$) to transport as many of its late evacuees as possible. The Table 6.9 results indicate that Bus 1 could also evacuate all 130 late evacuees from Taggerty ($i_3$) to the closest available shelter within the pre-defined bushfire time window of ($m = 4$) via four round trips. Finally, Bus 1 proceeds to the next adjacent township, Rubicon($i_6$), and it subsequently transports 180 of its late evacuees to the closest shelter at Thornton($j_2$), via four round trips. However, due to the limited capacity of Thornton ($j_2$) the remaining late evacuees from Rubicon ($i_6$) need to be transported to Alexandra ($j_1$) as the next adjacent shelter by bus 1. Therefore, the model determined that Bus 1 could only evacuate three hazardous townships (445 people) via the most reliable routes. However, evacuees on the other townships also need to be evacuated within their respective time windows.

In this manner, Bus 2 is assigned to start its evacuation service from Cambarville ($i_5$). The safest routing plan then is to transport one late evacuee group to Alexandra($j_1$), as the Thornton ($j_2$) shelter capacity is already at full capacity due to evacuees delivered by Bus 1. In returning to Cambarville($i_5$), Bus 2 subsequently transports one evacuee group from Marysville($i_2$), due to its shorter travelling distance and higher evacuee population. Interestingly, despite the longer distance for its last feasible service, Bus 2 is routed from Cambarville ($i_5$) to Eildon ($j_3$) via route two, in order to increase the reliability of routing against bushfire disruption. In a similar fashion to the examples it has been outlined for the townships serviced by Buses 1 and 2, the ideal feasible routing schedule for evacuation of the other townships are summarised in Table 6.9, along with the designated vehicles for each. Figure 6.17 depicts the evacuation routing pattern of assigned vehicles, with the route of each vehicle indicated by different colours.

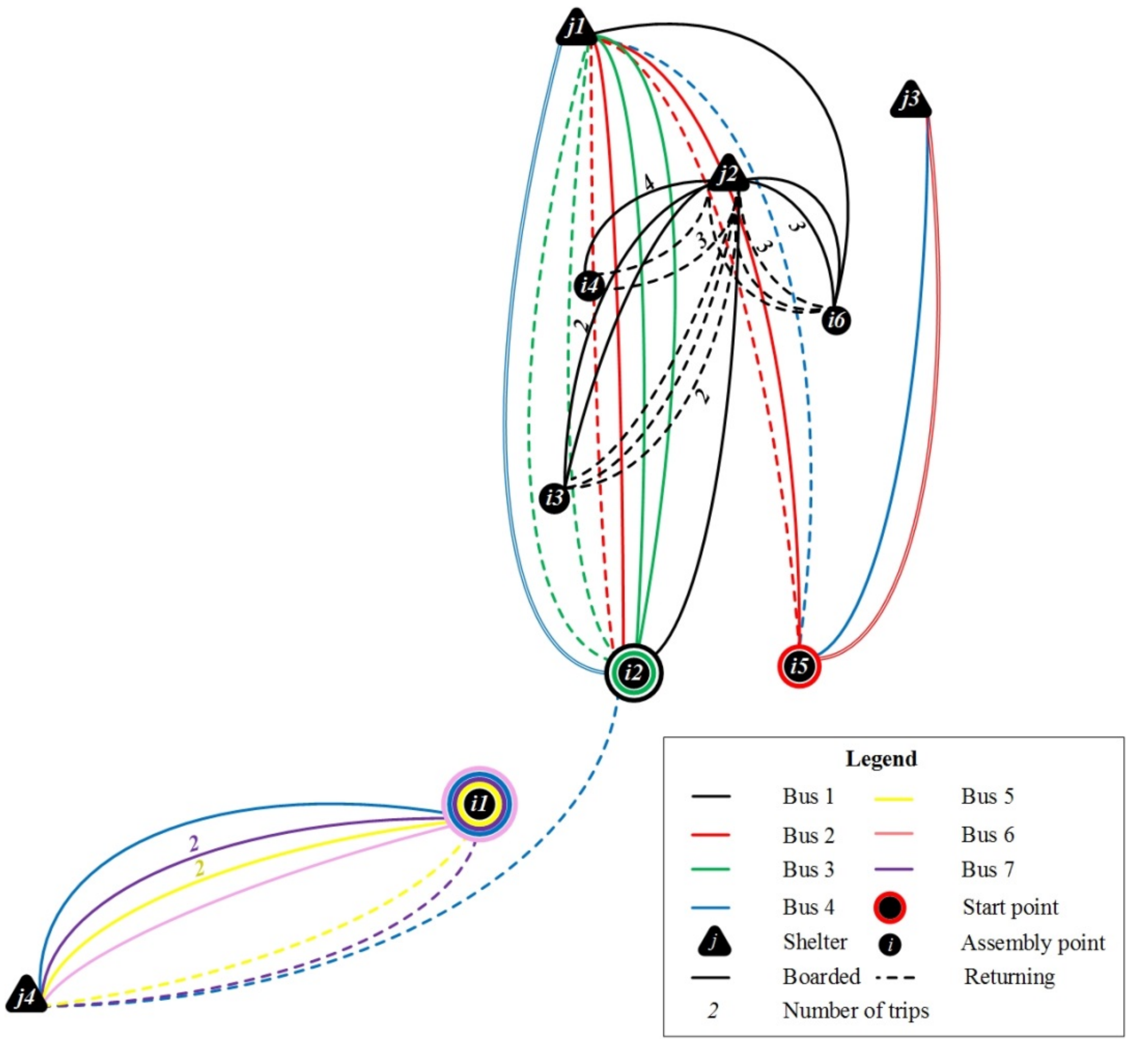



Figure 6.17 Vehicles routing pattern

The routing arrangement identified in Table 6.9 for each vehicle is illustrated in Figure 6.17. The start point of each vehicle is marked by a circle while the finish point is highlighted by a triangle. The solid lines indicate evacuee boarded vehicle trips while dashed lines indicate returning vehicle (empty) trips.

Figure 6.18 illustrates the arrangement of evacuation plan for the baseline.

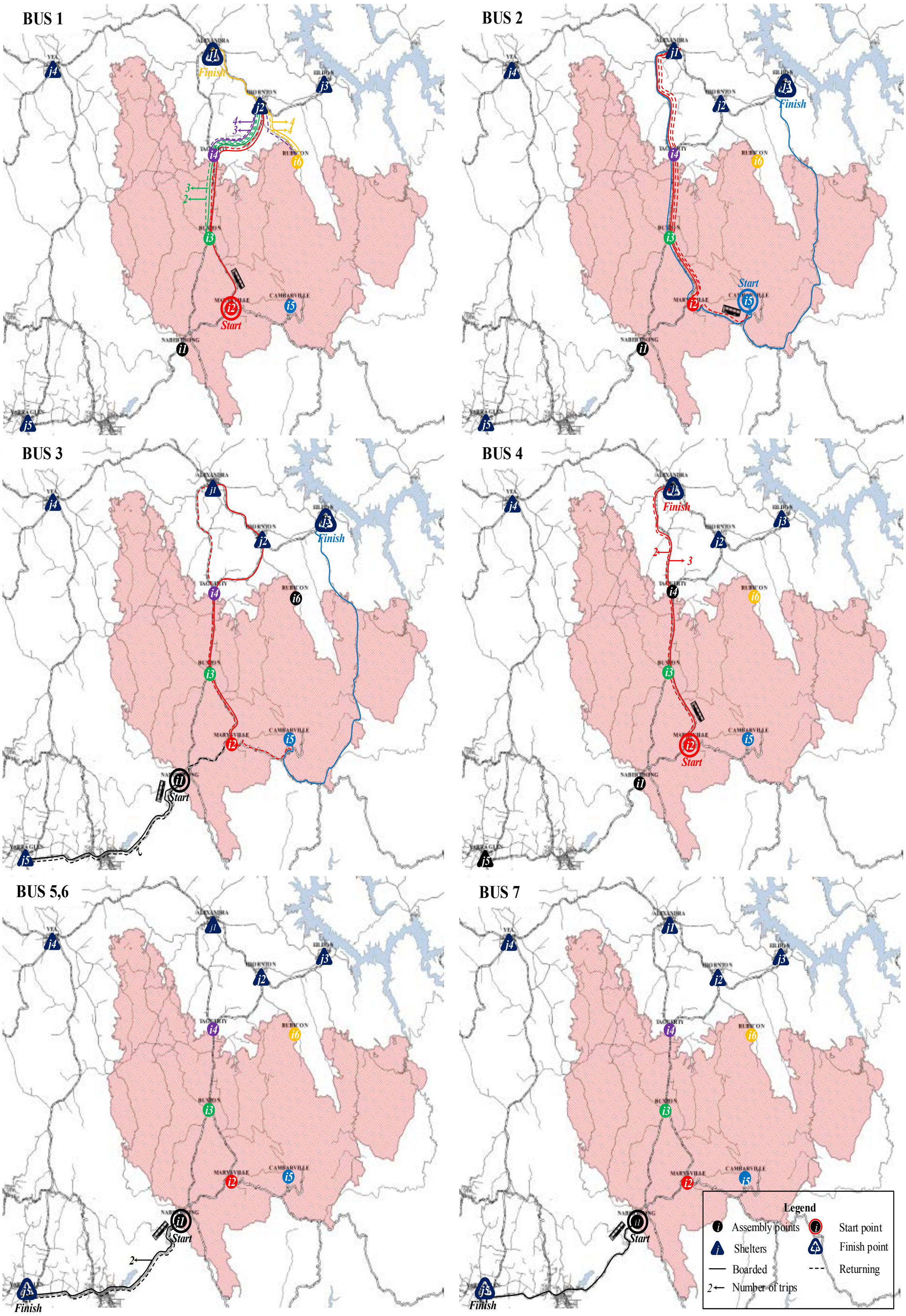



Figure 6.18 The arrangement of evacuation plan for the baseline.

The evacuation route for each township is depicted in a specific colour. Numbers on each route also show the number of trips in the route. The return routes are shown by dashed lines.

### 6.3.3 Scenario II: disruption in the high capacity shelter

The Alexandra shelter ($j_1$) with a capacity of 1500 people plays an important role in the late evacuation process (Figure 6.19). Approximately one quarter of the total number of late evacuees are transported to this shelter.

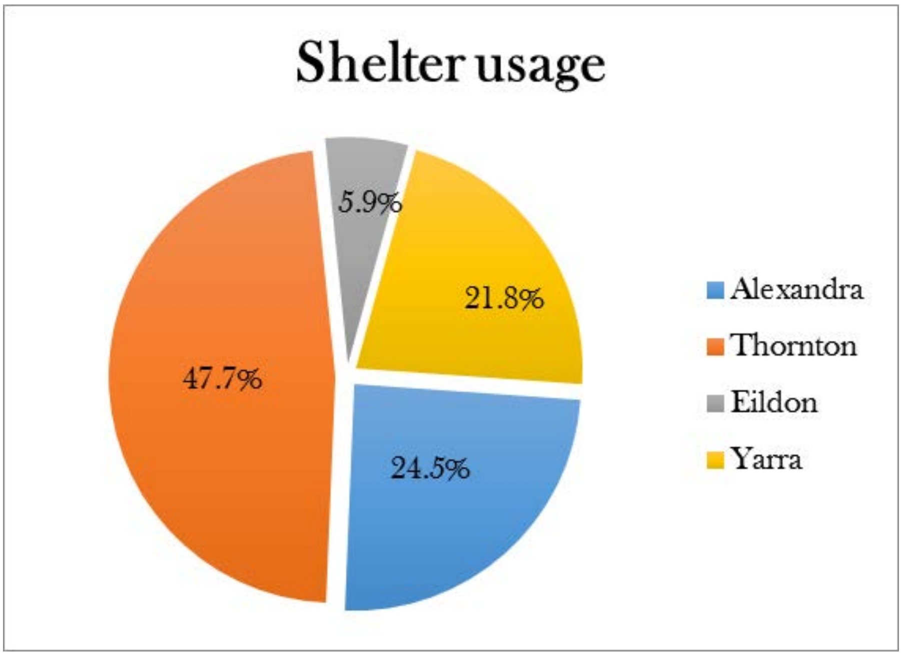



Figure 6.19 Shelter capacity usage

To analyse the impact of unforeseen disruption in the functioning shelters, in this scenario it is assumed that Alexandra is no longer available to shelter the late evacuees. As the results in Table 6.10 indicate, the model could route the available vehicles so that all people could still be evacuated. The only difference for Bus 1 in this scenario is the evacuation of the last group at Rubicon ($i_6$) due to Thornton being at full capacity. In the absence of Alexandra ($j_1$), the model has assigned Eildon ($j_3$) as the closest shelter to absorb the last Rubicon ($i_6$) late evacuees. Bus 2 service started from Narbethong ($i_1$) and proceeded to Yarra Glen($j_5$). This is followed by the evacuation of one group from Marysville ($i_2$) to Eildon ($j_3$) and finally from Cambarville ($i_5$) to Eildon ($j_3$) again. Due to the unavailability of the Alexandra shelter, the model has planned the routing schedules for five more buses in order to transport the entire late evacuee population ahead of the bushfire.

Table 6.10 The evacuation plan in a disruption to the central shelter scenario

| Vehicle | Time period | From | To | Route 1 | Route 2 | Route 3 | Transferred | | Lost evacuees | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Assembly point | Population | Assembly point | Population |
| Bus 1 | $m_1$ | Marysville | Thornton | × | | | Rubicon | 190 | Narbethong | 240 |
| | | Thornton | Taggerty | × | | | Taggerty | 170 | Marysville | 260 |
| | $m_2$ | Taggerty | Thornton | × | | | | | Buxton | 130 |
| | | Thornton | Buxton | × | | | | | Cambarville | 110 |
| | $m_3$ | Buxton | Thornton | × | | | | | | |
| | | Thornton | Buxton | × | | | | | | |
| | | Buxton | Thornton | × | | | | | | |
| | | Thornton | Taggerty | × | | | | | | |
| | | Buxton | Thornton | × | | | | | | |
| | | Thornton | Taggerty | × | | | | | | |
| | $m_4$ | Taggerty | Thornton | × | | | | | | |
| | | Thornton | Taggerty | × | | | | | | |
| | | Taggerty | Thornton | × | | | | | | |
| | | Thornton | Taggerty | × | | | | | | |
| | | Taggerty | Thornton | × | | | | | | |
| | | Thornton | Rubicon | × | | | | | | |
| | $m_5$ | Rubicon | Thornton | × | | | | | | |
| | | Thornton | Rubicon | × | | | | | | |
| | $m_6$ | Rubicon | Thornton | × | | | | | | |
| | | Thornton | Rubicon | × | | | | | | |
| | | Rubicon | Thornton | × | | | | | | |
| | | Thornton | Rubicon | × | | | | | | |
| | | Rubicon | Thornton" | × | | | | | | |
| | | Thornton | Rubicon | × | | | | | | |
| | | Rubicon | Eildon | | × | | | | | |
| Bus 2 | $m_1$ | Marysville | Yarra | × | | | Narbethong | 45 | Narbethong | 195 |
| | | Yarra | Marysville | × | | | Marysville | 90 | Marysville | 170 |
| | $m_2$ | Marysville | Eildon | × | | | Buxton | 130 | Cambarville | 65 |
| | | Eildon | Cambarville | × | | | Cambarville | 45 | | |
| | $m_3$ | Cambarville | Eildon | | × | | | | | |
| Bus 3 | $m_1$ | Marysville | Yarra | × | | | Narbethong | 45 | Narbethong | 150 |
| | | Yarra | Marysville | × | | | Marysville | 45 | Marysville | 125 |
| | $m_2$ | Marysville | Eildon | × | | | Cambarville | 45 | Cambarville | 20 |
| | | Eildon | Cambarville | × | | | | | | |
| | $m_3$ | Cambarville | Eildon | | × | | | | | |
| Bus 4 | $m_1$ | Marysville | Yarra | × | | | Narbethong | 45 | Narbethong | 105 |
| | | Yarra | Marysville | × | | | Marysville | 45 | Marysville | 80 |
| | $m_2$ | Marysville | Eildon | × | | | Cambarville | 20 | | |
| | | Eildon | Cambarville | × | | | | | | |
| | | Cambarville | Eildon | | × | | | | | |
| Bus 5 | $m_1$ | Marysville | Eildon | × | | | Marysville | 80 | Narbethong | 105 |
| | | Eildon | Marysville | × | | | | | | |
| | | Marysville | Eildon | × | | | | | | |
| Bus 6 | $m_1$ | Narbethong | Yarra | × | | | Narbethong | 90 | Narbethong | 15 |
| | | Yarra | Narbethong | × | | | | | | |
| | | Narbethong | Yarra | × | | | | | | |
| Bus 7 | $m_1$ | Narbethong | Yarra | × | | | Narbethong | 15 | | 0 |
| Total | | | | | | | | 1100 | | |

Figure 6.20 depicts the arrangement of the evacuation plan under this central shelter functioning failure scenario.

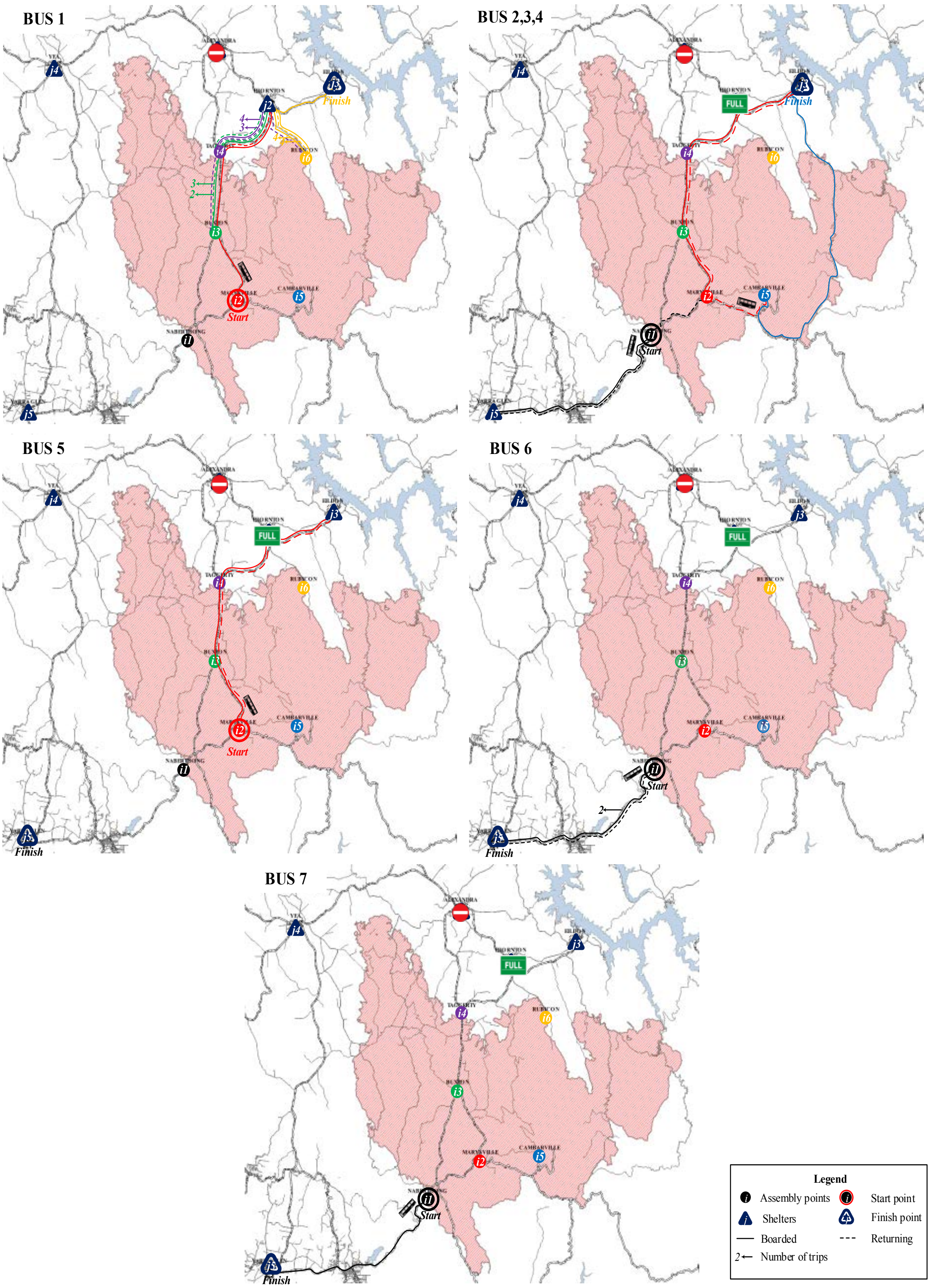



Figure 6.20 Evacuation routing pattern in a central shelter disruption scenario.

The evacuation route for each township is depicted in a specific colour. Numbers on each route also show the number of trips in the route. The return routes are shown by dashed lines.

### 6.3.4 Scenario III: disruption in both highly used road and shelter

As noted earlier, the availability of infrastructure during wildfires remains one of the most challenging issues for emergency evacuation services. The analyses of the results discussed in the last Section indicate that the Maroondah Highway as the major road route between Buxton and Taggerty (coded as $l_{17}$ in the Figure 3.5), plays a critical role in all routing plans. More than half of the late evacuees (57.27 per cent) are evacuated to the northern shelters via the Maroondah Highway. On Black Saturday in 2009, police reported doubts over the accessibility of the Maroondah Highway.

Wildfires potentially may not only disrupt route accessibility but may also affect shelter availability. As Figure 6.18 indicates, approximately half of the entire late evacuee population is accommodated in Thornton $(j_2)$ (47.7 per cent), due to its central location. Hence, this Section aims to investigate the model's ability to generate the routing plans in a scenario of both route and shelter disruption. In this case it is assumed that the Maroondah Highway is no longer available due to a collision immediately after bushfire ignition on the right side of the network. In addition, due to unforeseen operational failures, it is assumed that Thornton is not functioning as an available shelter.

Table 6.11 indicates that Bus 1 is scheduled to depart from Rubicon $(i_6)$ to Alexandra $(j_1)$. Bus 1 then returns to Taggerty $(i_3)$ to evacuate its entire population of late evacuees via four round trips. It is notable that route 2 between Taggerty $(i_3)$ and Alexandra $(j_1)$ has a higher reliability against bushfire disruption and has been assigned to route the departure bus trips from Taggerty. In the same way, the evacuation routing plans for other townships can be observed in Table 6.11.

Table 6.11 Evacuation plan in a disruption to both the major road route and the most used shelter scenario

| | | | | | | | Transferred | | Lost evacuees | |
|---|---|---|---|---|---|---|---|---|---|---|
| Vehicle | Time period | From | To | Route 1 | Route 2 | Route 3 | Assembly point | Population | Assembly point | Population |
| Bus 1 | $\square_1$ | Rubicon | Alexandra | × | | | Rubicon | 190 | Narbethong | 240 |
| | | Alexandra | Taggerty | × | | | Taggerty | 170 | Marysville | 260 |
| | $m_2$ | Taggerty | Alexandra* | | × | | | | Buxton | 130 |
| | | Alexandra | Taggerty | × | | | | | Cambarville | 110 |
| | | Taggerty | Alexandra | | × | | | | | |
| | | Alexandra | Taggerty | × | | | | | | |
| | | Taggerty | Alexandra | | × | | | | | |
| | | Alexandra | Taggerty | × | | | | | | |
| | $m_3$ | Taggerty | Alexandra | | × | | | | | |
| | | Alexandra | Rubicon | × | | | | | | |
| | $m_4$ | Rubicon | Alexandra | × | | | | | | |
| | | Alexandra | Rubicon | × | | | | | | |
| | $m_5$ | Rubicon | Alexandra | × | | | | | | |
| | | Alexandra | Rubicon | × | | | | | | |
| | $m_6$ | Rubicon | Alexandra | × | | | | | | |
| | | Alexandra | Rubicon | × | | | | | | |
| | | Rubicon | Alexandra | × | | | | | | |
| Bus 2 | $m_1$ | Narbethong | Yarra | × | | | Narbethong | 45 | Narbethong | 195 |
| | | Yarra | Marysville | × | | | Marysville | 45 | Marysville | 215 |
| | $m_2$ | Marysville | Yarra | × | | | Buxton | 45 | Buxton | 85 |
| | | Yarra | Buxton | × | | | Cambarville | 45 | Cambarville | 65 |
| | $m_3$ | Buxton | Yarra | × | | | | | | |
| | | Yarra | Cambarville | × | | | | | | |
| | $m_4$ | Cambarville | Eildon* | | × | | | | | |
| Bus 3 | $m_1$ | Narbethong | Yarra | × | | | Narbethong | 45 | Narbethong | 150 |
| | | Yarra | Marysville | × | | | Marysville | 45 | Marysville | 170 |
| | $m_2$ | Marysville | Yarra | × | | | Buxton | 45 | Buxton | 40 |
| | | Yarra | Buxton | × | | | Cambarville | 45 | Cambarville | 20 |
| | $m_3$ | Buxton | Yarra | × | | | | | | |
| | | Yarra | Cambarville | × | | | | | | |
| | $m_4$ | Cambarville | Eildon* | | × | | | | | |
| Bus 4 | $m_1$ | Narbethong | Yarra | × | | | Narbethong | 45 | Narbethong | 105 |
| | | Yarra | Marysville | × | | | Marysville | 45 | Marysville | 125 |
| | $m_2$ | Marysville | Yarra | × | | | Buxton | 40 | | |
| | | Yarra | Buxton | × | | | Cambarville | 20 | | |
| | $m_3$ | Buxton | Yarra | × | | | | | | |
| | | Yarra | Cambarville | × | | | | | | |
| | $m_4$ | Cambarville | Eildon* | | × | | | | | |
| Bus 5 | $m_1$ | Narbethong | Yarra | × | | | Narbethong | 45 | Narbethong | 60 |
| | | Yarra | Marysville | × | | | Marysville | 45 | Marysville | 80 |
| | $m_2$ | Marysville | Yarra | × | | | | | | |
| Bus 6 | $m_1$ | Narbethong | Yarra | × | | | Narbethong | 45 | Narbethong | 15 |
| | | Yarra | Marysville | × | | | Marysville | 45 | Marysville | 35 |
| | $m_2$ | Marysville | Yarra | × | | | | | | |
| Bus 7 | $m_1$ | Narbethong | Yarra | × | | | Narbethong | 15 | | |
| | | Yarra | Marysville | × | | | Marysville | 35 | | 0 |
| | $m_2$ | Marysville | Yarra | × | | | | | | |
| Total | | | | | | | | 1100 | | |

Furthermore, Figure 6.21 visualises the arrangement of the evacuation plan under this disruptions scenario.

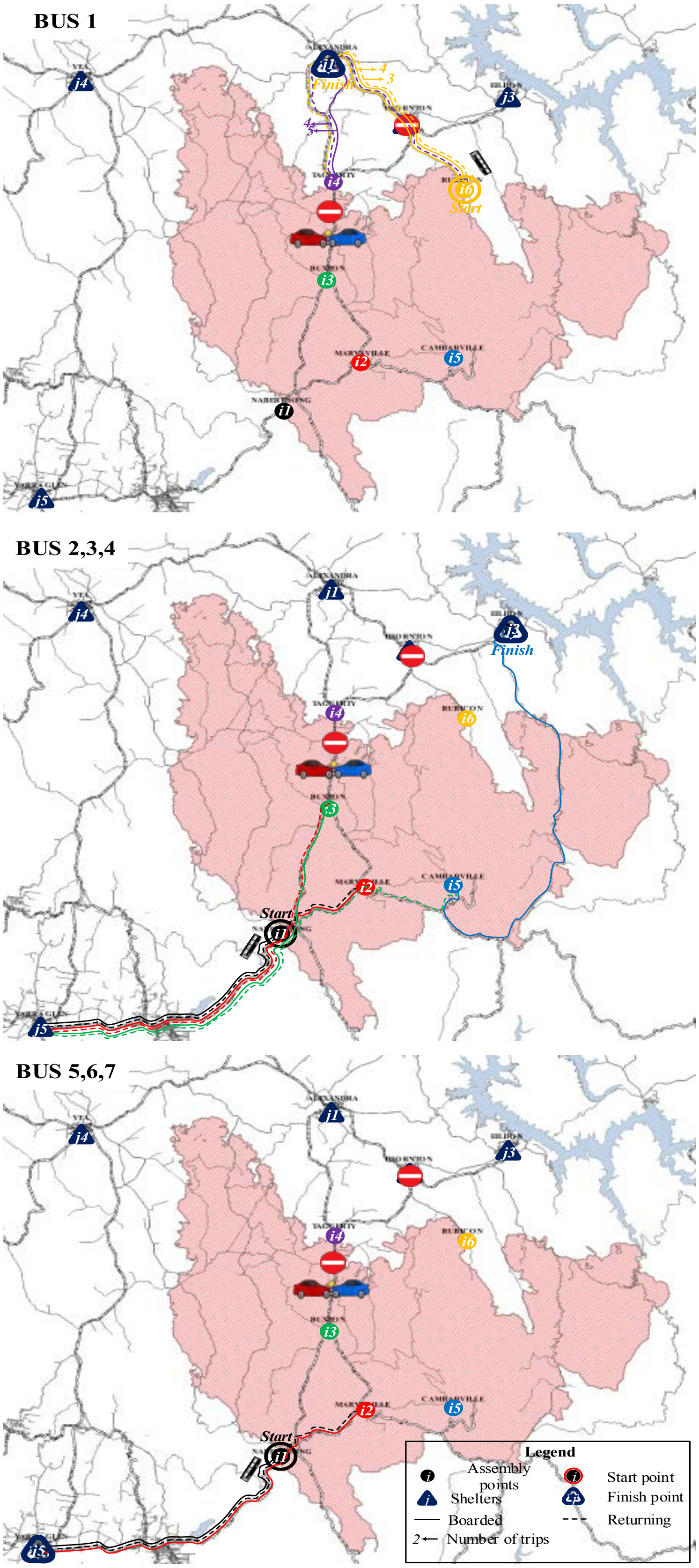



Figure 6.21 Evacuation routing pattern under both road and shelter disruptions

The evacuation route for each township is depicted in a specific colour. Numbers on each route also show the number of trips in the route. The return routes are shown by dashed lines.

Therefore, even considering severe disruption in the most highly used network infrastructure (the major road route and the most used shelter), the model is able to provide routing arrangements to maximise evacuation. The entire late evacuee population could still be evacuated within the time windows via the same seven buses. That is, there is no change necessary to the number of assigned buses in comparison to an “ideal” evacuation situation (i.e. with no route or shelter disruptions). However, the objective function value decreases to 590 (Table 6.12). This drop in the total objective function is due to the limitation of re-routing the buses by assigning routes with higher disruption risks compared to the previous scenarios. In addition, travelling longer distances to reach available functioning shelters might have been effective. Table 6.12 also provides a summary of the objective functions for each vehicle under each scenario.

Table 6.12 The objective function values

| **Vehicle** | **Scenario I** | **Scenario II** | **Scenario III** |
|---|---|---|---|
| Bus 1 | 269.16 | 266.43 | 186 |
| Bus 2 | 91.82 | 73.08 | 113.89 |
| Bus 3 | 73.07 | 73.08 | 89.95 |
| Bus 4 | 67.05 | 73.08 | 89.95 |
| Bus 5 | 43.6 | 42.84 | 45.5 |
| Bus 6 | 46.62 | 46.62 | 45.5 |
| Bus 7 | 23.31 | 23.31 | 45.5 |
| Total | 614.63 | 598.44 | 590 |

## 6.4 Model III: P-CMDVRP-TW

This section provides explanation of the application of the third model on three bushfire scenario. It is notable that since the third model's formulation is similar to the model II, the model effectiveness is already validated.

### 6.4.1 Scenario I: Baseline

The evacuation plan is successfully implemented via utilising seven rescue buses to transport evacuees to four safe shelters (Table 6.13). Bus 1 starts its evacuee pick-up service from Marysville, transporting its first passengers to the closest available shelter at Thornton, via the safest route. Due to the short traveling distance and clearance time, Bus 1 is unable to return to Marysville to pick-up further evacuees from that township, Instead, Bus 1 leaves Thornton and to pick-up evacuees from Buxton. Buxton has the least clearance time for bushfire propagation behind Narbethong and Marysville. Table 6.13 outlines the routing schedule and designated rescue vehicles for the evacuation of the other towns and illustrates that three round trips via the lowest risk route one are necessary in order to rescue all 130 late evacuees from Buxton prior to the bushfire engulfing the town.

Table 6.13 The evacuation plan in the baseline

| Vehicle | Time period | From | To | Route 1 | Route 2 | Route 3 | Transferred: Assembly point | Transferred: Population | Lost evacuees: Assembly point | Lost evacuees: Population |
|---|---|---|---|---|---|---|---|---|---|---|
| Bus 1 | $m_1$ | Marysville | Thornton | × | | | | | | |
| | | Thornton | Buxton | × | | | | | | |
| | $m_2$ | Buxton | Thornton | × | | | | | | |
| | | Thornton | Buxton | × | | | | | | |
| | | Buxton | Thornton | × | | | | | | |
| | | Thornton | Buxton | × | | | | | | |
| | $m_3$ | Buxton | Thornton | × | | | Rubicon | 190 | Narbethong | 240 |
| | | Thornton | Rubicon | × | | | Marysville | 45 | Marysville | 215 |
| | $m_4$ | Rubicon | Thornton | × | | | Taggerty | 170 | Cambarville | 110 |
| | | Thornton | Taggerty | × | | | Buxton | 130 | | |
| | | Taggerty | Alexandra | × | | | | | | |
| | | Alexandra | Taggerty | × | | | | | | |
| | | Taggerty | Alexandra | × | | | | | | |
| | | Alexandra | Taggerty | × | | | | | | |
| | | Taggerty | Alexandra | × | | | | | | |
| | | Alexandra | Taggerty | × | | | | | | |
| | | Taggerty | Alexandra | × | | | | | | |
| | | Alexandra | Rubicon | × | | | | | | |
| | $m_5$ | Rubicon | Thornton | × | | | | | | |
| | | Thornton | Rubicon | × | | | | | | |
| | $m_6$ | Rubicon | Thornton | × | | | | | | |
| | | Thornton | Rubicon | × | | | | | | |
| | | Rubicon | Thornton | × | | | | | | |
| | | Thornton | Rubicon | × | | | | | | |
| | | Rubicon | Thornton | × | | | | | | |
| Bus 2 | $m_1$ | Narbethong | Yarra | × | | | | | | |
| | | Yarra | Marysville | × | | | Narbethong | 45 | Narbethong | 195 |
| | $m_2$ | Marysville | Thornton | × | | | Marysville | 45 | Marysville | 170 |
| | | Thornton | Cambarville | × | | | Cambarvill | 90 | Cambarville | 20 |
| | $m_3$ | Cambarville | Thornton* | × | | | | | | |
| | | Thornton | Cambarville | × | | | | | | |
| | | Cambarville | Alexandra | × | | | | | | |
| Bus 3 | $m_1$ | Narbethong | Yarra | × | | | | | | |
| | | Yarra | Marysville | × | | | Narbethong | 45 | Narbethong | 150 |
| | $m_2$ | Marysville | Alexandra | | × | | Marysville | 45 | Marysville | 125 |
| | | Alexandra | Cambarville | × | | | Cambarvill | 20 | | |
| | $m_3$ | Cambarville | Eildon | | × | | | | | |
| Bus 4 | $m_1$ | Narbethong | Yarra | × | | | | | | |
| | | Yarra | Marysville | × | | | Narbethong | 45 | Narbethong | 105 |
| | $m_2$ | Marysville | Alexandra | × | | | Marysville | 90 | Marysville | 35 |
| | | Alexandra | Marysville | × | | | | | | |
| | | Marysville | Alexandra | × | | | | | | |
| Bus 5 | $m_1$ | Narbethong | Yarra | × | | | | | | |
| | | Yarra | Marysville | | × | | Narbethong | 45 | Narbethong | 60 |
| | | Marysville | Alexandra | × | | | Marysville | 35 | | |
| Bus 6 | $m_1$ | Narbethong | Yarra | × | | | | | | |
| | | Yarra | Narbethong | × | | | Narbethong | 60 | | |
| | | Narbethong | Yarra | × | | | | | | |
| Total | | | | | | | | 1100 | | |

After delivering the last of the Buxton late evacuees to Thornton, Bus 1 travels to Taggerty in order to pick-up as many of its late evacuees as its capacity will allow. Table 6.13 demonstrates that Bus 1 could transport all 130 late evacuees from Taggerty to the closest available shelter via four round trips, within the pre-defined bushfire clearance time. Bus 1's final rescue trips are to the shelter in the adjacent town of Rubicon. Four round trips are necessary to transport Rubicon's 180 late evacuees to the closest safe shelters at firstly Thornton, and then to Alexandra, once Thornton reaches its maximum capacity of evacuees. The model determined that Bus 1 could utilise the most reliable routes in order to safely transport all late evacuees from three bushfire-impacted towns (440 people). However, the late evacuees in other bushfire-affected towns also need to be safely transported within their respective clearance times. The model assigns Bus 2 to start its evacuation rescue pick-up service from the township at Cambarville. Given that the Thornton safe shelter is already at full capacity due to evacuees being delivered by Bus 1, Bus 2 evacuates one late Cambarville group to Alexandra. Bus 2 then transports one Marysville evacuee group, due to the higher evacuee population at this township and the short travelling distance between Marysville and Alexandra. In order to increase the reliability of routing versus the risk of bushfire disruption, for its last rescue pick-up service the model routes Bus 2 from Cambarville to Eildon via route two, despite the longer distance. Table 6.14 shows the overall degree of satisfaction followed by objective function, NIS, PIS values. Using the strategy to maximise the total objective function and at the discretion of decision maker to adjust the probabilities, the overall decision maker's satisfaction degree increased from 0.695 to 0.825. Table 6.15 provides degrees of satisfaction by each bus.

Table 6.14 Overall degree of satisfaction

| | **Initial solution** | **Improved solution** |
|---|---|---|
| Overall degree of satisfaction (λ) | 0.695 | 0.825 |
| Objective values | (608.79, 63.19, 136.33) | (614.79, 65.92, 132.67) |
| NIS (initial solution) | (347.21, 149.05, 55.45) | (323.46, 156.05, 51.43) |
| PIS (initial solution) | (617.35, 62.42, 133.32) | (615.27, 61.02, 138.32) |

Table 6.15 Degrees of satisfaction by each bus

| **Vehicle** | **PIS** | **NIS** | $\lambda$ |
|---|---|---|---|
| Bus 1 | (285.36, 25.7, 65.12) | (97,51, 80.92, 9.75) | 0.729 |
| Bus 2 | (92.73, 11.94, 19.08) | (62.02, 19.02, 11.94) | 0.786 |
| Bus 3 | (73.71, 12.19, 17.70) | (61.47, 14.70, 12.19) | 0.738 |
| Bus 4 | (67.05, 8.86, 14.02) | (38.31, 14.02, 8.86) | 0.759 |
| Bus 5 | (44.39, 8.81, 10.12) | (38.315, 10.21, 8.81) | 0.852 |
| Bus 6 | (46.62, 4.33, 10.16) | (19.57, 10.16, 4.33) | 0.76 |

Figure 6.22 outlines the evacuation plan for the baseline. The route of each rescue vehicles indicated via different colours.

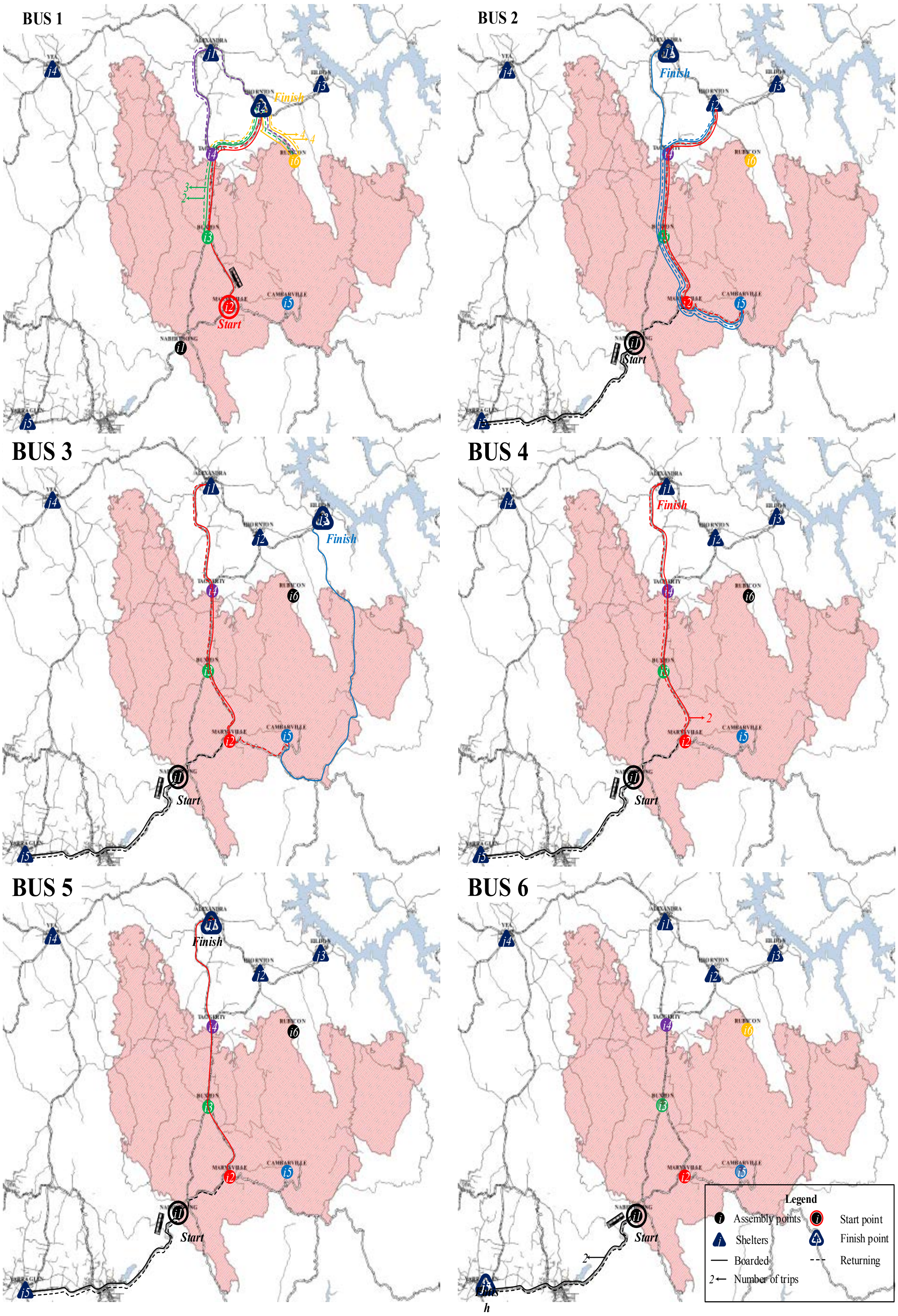



Figure 6.22 Optimal routing arrangement on the Possibilistic model.

### 6.4.2 Scenario II: disruption in the high capacity shelter

The analysis of results from previous section shows that the Alexandra shelter plays a crucial role in the late-evacuation process. Approximately 25 per cent of all late evacuees are transported to the Alexandra shelter. In this scenario, it is assumed that Alexandra is not available as a safe shelter for late evacuees. This therefore allows for the impact of an unforeseen disruption to a key shelter to be analysed. Table 6.16 demonstrates that the model re-routes the available rescue bus vehicles to enable the safe transport of all late evacuees to the remaining safe shelters. The only change for Bus 1 compared to the previous “ideal” scenario (i.e. when there is no infrastructure disruptions) is that the last group of evacuees at Rubicon are transported to Eildon as the closest available safe shelter, in the absence of Alexandra and with Thornton already being at full capacity. The Bus 2 evacuation service starts via a pick-up from Narbethong to safely transport evacuees to the safe shelter at Yarra Glen. Next, Bus 2 evacuates a group from Marysville to Eildon and as its final service it transports evacuees from Cambarville to Eildon. With the Alexandra shelter being unavailable, the model plans the routing schedules for five more buses in order to safely transport the entire late evacuee population to the remaining safe shelters.

Table 6.16 The evacuation plan in a disruption to the central shelter scenario

| Vehicle | Time period | From | To | Route 1 | Route 2 | Route 3 | Transferred | | Lost evacuees | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Assembly point | Population | Assembly point | Population |
| Bus 1 | $m_1$ | Marysville | Thornton | × | | | | | | |
| | | Thornton | Buxton | × | | | | | | |
| | $m_2$ | Buxton | Thornton | × | | | | | | |
| | | Thornton | Buxton | × | | | | | | |
| | | Buxton | Thornton | × | | | | | | |
| | | Thornton | Buxton | × | | | | | | |
| | | Buxton | Thornton | × | | | Rubicon | 190 | Narbethong | 240 |
| | | Thornton | Taggerty | × | | | Marysville | 45 | Marysville | 215 |
| | | Taggerty | Thornton | × | | | Taggerty | 170 | Cambarville | 110 |
| | | Thornton | Taggerty | × | | | Buxton | 130 | | |
| | | Taggerty | Thornton | × | | | | | | |
| | | Thornton | Taggerty | × | | | | | | |
| | $m_3$ | Taggerty | Thornton | × | | | | | | |
| | | Thornton | Taggerty | × | | | | | | |
| | $m_4$ | Taggerty | Thornton | × | | | | | | |
| | | Thornton | Rubicon | × | | | | | | |
| | $m_5$ | Rubicon | Thornton | × | | | | | | |
| | | Thornton | Rubicon | × | | | | | | |
| | $m_6$ | Rubicon | Thornton | × | | | | | | |
| | | Thornton | Rubicon | × | | | | | | |
| | | Rubicon | Thornton | × | | | | | | |
| | | Thornton | Rubicon | × | | | | | | |
| | | Rubicon | Thornton | × | | | | | | |
| | | Thornton | Rubicon | × | | | | | | |
| | | Rubicon | Eildon | × | | | | | | |
| Bus 2 | $m_1$ | Narbethong | Yarra | × | | | | | | |
| | | Yarra | Marysville | × | | | Narbethong | 45 | Narbethong | 195 |
| | $m_2$ | Marysville | Eildon | × | | | Marysville | 45 | Marysville | 170 |
| | | Eildon | Cambarville | × | | | Cambarville | 45 | Cambarville | 65 |
| | $m_3$ | Cambarville | Eildon | | × | | | | | |
| Bus 3 | $m_1$ | Narbethong | Yarra | × | | | | | | |
| | | Yarra | Marysville | × | | | Narbethong | 45 | Narbethong | 150 |
| | $m_2$ | Marysville | Eildon | × | | | Marysville | 45 | Marysville | 125 |
| | | Alexandra | Cambarville | × | | | Cambarville | 45 | Cambarville | 20 |
| | $m_3$ | Cambarville | Eildon" | | × | | | | | |
| Bus 4 | $m_1$ | Narbethong | Yarra | × | | | | | | |
| | | Yarra | Marysville | × | | | Narbethong | 45 | Narbethong | 105 |
| | $m_2$ | Marysville | Eildon | × | | | Marysville | 45 | Marysville | 80 |
| | | Eildon | Cambarville | × | | | Cambarville | 20 | | |
| | $m_3$ | Cambarville | Eildon" | | × | | | | | |
| Bus 5 | $m_1$ | Narbethong | Yarra | × | | | | | | |
| | | Yarra | Marysville | × | | | Narbethong | 45 | Narbethong | 60 |
| | $m_2$ | Marysville | Yea | × | | | Marysville | 45 | Marysville | 35 |
| Bus 6 | $m_1$ | Narbethong | Yarra | × | | | | | | |
| | | Yarra | Marysville | | × | | Narbethong | 45 | Narbethong | 15 |
| | $m_2$ | Marysville | Yea | × | | | Marysville | 35 | | |
| Bus 7 | $m_1$ | Narbethong | Yarra | × | | | Narbethong | 15 | | |
| Total | | | | | | | | 1100 | | |

### 6.4.3 Scenario III: disruption in both highly used road and shelter

One of the major challenges that emergency evacuation services face during bushfires is the availability of infrastructure. In the Murrindindi Mill case study, the Maroondah Highway plays a critical role in all routing plans. It is the major road route between

Buxton and Taggerty, and in the “ideal” scenario, is utilised for the transport of 57.27 percent of evacuees to the safe northern shelters. Therefore, the model’s ability to generate the routing plans in a scenario of both route and shelter disruption needs to be examined. Result indicates that in the “ideal” scenario nearly half of the late evacuee population is accommodated in Thornton, due to its central location. In this Scenario II, it is assumed that Thornton is not available as a functioning safe shelter due to operational failures. In addition, the Maroondah Highway is not available on the right side of the network due to a major vehicle accident shortly after the bushfire ignited. In this dual disruption scenario, Bus 1 is scheduled to travel from Rubicon to Alexandra. It then returns to Taggerty to evacuate all of its late evacuees via four round trips. Route 2 has been assigned between Taggerty and Alexandra due to higher reliability against bushfire disruption. Table 6.17 similarly outlines the evacuation routing plans for other affected towns under this dual disruption scenario. Therefore, it can be argued that the model is capable of providing routing plans to maximise the transfer of evacuees to safe shelters even when there are severe disruptions in the most highly used network infrastructure (i.e. the major road route and the most used shelter). The same seven buses from the Baseline scenario could still be effectively utilised to safely transport the entire late evacuee population within the clearance times. However, the objective function value decreases to 0.59 in this dual disruption scenario. This decrease is due to the re-routing of buses to routes with higher disruption risks. Routing the buses via longer, safer distances to reach the remaining available functioning shelters might have been more effective.

Table 6.17 Evacuation plan in a disruption to both the major road route and the most used shelter scenario

| Vehicle | Time period | From | To | Route 1 | Route 2 | Route 3 | Transferred | | Lost evacuees | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | Assembly point | Population | Assembly point | Population |
| Bus 1 | $m_1$ | Rubicon | Alexandra | | × | | | | | |
| | | Alexandra | Taggerty | × | | | | | | |
| | $m_2$ | Taggerty | Alexandra | | × | | | | | |
| | | Alexandra | Taggerty | × | | | | | | |
| | | Taggerty | Alexandra | | × | | | | | |
| | | Alexandra | Taggerty | × | | | | | | |
| | | Taggerty | Alexandra | | × | | Rubicon | 190 | Narbethong | 240 |
| | | Alexandra | Taggerty | × | | | Taggerty | 170 | Marysville | 260 |
| | $m_3$ | Taggerty | Alexandra | | × | | | | Buxton | 130 |
| | | Alexandra | Rubicon | × | | | | | Cambarville | 110 |
| | $m_4$ | Rubicon | Alexandra | × | | | | | | |
| | | Alexandra | Rubicon | × | | | | | | |
| | $m_5$ | Rubicon | Alexandra | × | | | | | | |
| | | Alexandra | Rubicon | × | | | | | | |
| | $m_6$ | Rubicon | Alexandra | × | | | | | | |
| | | Alexandra | Rubicon | × | | | | | | |
| | | Rubicon | Alexandra | × | | | | | | |
| Bus 2 | $m_1$ | Narbethong | Yarra | × | | | | | | |
| | | Yarra | Marysville | × | | | Narbethong | 45 | Narbethong | 195 |
| | $m_2$ | Marysville | Yarra | × | | | Marysville | 45 | Marysville | 215 |
| | | Yarra | Buxton | × | | | Buxton | 45 | Buxton | 85 |
| | $m_3$ | Buxton | Yarra | × | | | Cambarville | 45 | Cambarville | 65 |
| | | Yarra | Cambarville | × | | | | | | |
| | $m_4$ | Cambarville | Yarra | × | | | | | | |
| Bus 3 | $m_1$ | Narbethong | Yarra | × | | | | | | |
| | | Yarra | Marysville | × | | | Narbethong | 45 | Narbethong | 150 |
| | $m_2$ | Marysville | Yarra | × | | | Marysville | 45 | Marysville | 170 |
| | | Yarra | Buxton | × | | | Buxton | 45 | Buxton | 40 |
| | $m_3$ | Buxton | Yarra | × | | | Cambarville | 45 | Cambarville | 20 |
| | | Yarra | Cambarville | × | | | | | | |
| | $m_4$ | Cambarville | Yarra | × | | | | | | |
| Bus 4 | $m_1$ | Narbethong | Yarra | × | | | | | | |
| | | Yarra | Marysville | × | | | Narbethong | 45 | Narbethong | 105 |
| | $m_2$ | Marysville | Yarra | × | | | Marysville | 45 | Marysville | 125 |
| | | Yarra | Buxton | × | | | Buxton | 40 | | |
| | $m_3$ | Buxton | Yarra | × | | | Cambarville | 20 | | |
| | | Yarra | Cambarville | × | | | | | | |
| | $m_4$ | Cambarville | Yarra | × | | | | | | |
| Bus 5 | $m_1$ | Narbethong | Yarra | × | | | | | | |
| | | Yarra | Marysville | × | | | Narbethong | 45 | Narbethong | 60 |
| | $m_2$ | Marysville | Yarra | × | | | Marysville | 45 | Marysville | 80 |
| Bus 6 | $m_1$ | Narbethong | Yarra | × | | | | | | |
| | | Yarra | Marysville | × | | | Narbethong | 45 | Narbethong | 15 |
| | $m_2$ | Marysville | Yarra | × | | | Marysville | 45 | Marysville | 35 |
| Bus 7 | $m_1$ | Narbethong | Yarra | × | | | | | | |
| | | Yarra | Marysville | × | | | Narbethong | 15 | | 0 |
| | $m_2$ | Marysville | Yarra | × | | | Marysville | 35 | | |
| Total | | | | | | | | 1100 | | |

## 6.5 Summary

In this chapter, a set of numerical analyses were designed and conducted to evaluate the developed mathematical formulations in order to optimise the stated short-notice evacuation problem. Three different scenarios were considered based on the 2009 Black Saturday bushfires to analyse the effects of the different bushfire situation. The models optimise the number of transferred evacuees, vehicle utilisation, shelter allocation and optimal routing.

The results of the models show the possibility of transferring all evacuees within the restricted time windows under different scenarios including baseline, minor and major network disruptions. Results showed that it would be possible to evacuate all late evacuees during the 2009 Black Saturday bushfire events, even if one or two resources are disrupted within the hard time window constraint by application of models.

Overall, the LEBMD-TW model efficiently assigned available shelters to absorb all 1,100 late evacuees transferred from assembly points in the bushfire affected areas by a fleet of five buses and twelve vans. The CMDVRP-TW model suggests the evacuation of late evacuees by seven rescue vehicles in four shelters is feasible. A decrease in the number of assigned vehicles is possible, however, it increases the risk of transporting evacuees via high-risk routes. The P-CMDVRP-TW model generated optimal routes and evacuation solutions under uncertainty and hard constraints. It was possible to evacuate equal numbers of evacuees by using only six buses and four shelters under low disruption risk. The P-CMDVRP-TW model under disruption scenarios generated an evacuation plan to transfer all late evacuees with seven buses and four shelters.

The next chapter will discuss the key findings of this research and revisit the research questions.

# Chapter 7

# Conclusion and future research

## 7.1 Introduction

This chapter discusses general conclusions and key findings from the analysis derived from each model. The models proved capable of providing the appropriate evacuation patterns that maximise emergency evacuation efficiency, including when hedging against significant infrastructure disruption risks. The subsequent sections discuss how the research questions underpinning this thesis are answered and makes an assessment of the implications of research. The key limitations of the research and opportunities for future research are discussed in the penultimate section. Finally, a summary of the chapter is presented to provide the final remarks of the key findings.

## 7.2 Key research findings

This section succinctly presents the key conclusions from the findings derived from the modelling. These are discussed for each of the models in the following sub-sections.

### 7.2.1 Model I: LEBMD-TW

The mixed-integer linear programming with multiple objectives for conflict resolution in bushfire emergency evacuation situation was implemented using the Late Evacuation Bushfire with Time Windows Multiple Destinations (LEBMD-TW) model. The LEBMD-TW model generated solutions that, in the context of bushfire scenario, maximised the number of people transferred from affected areas to safer places, whilst minimising overall assignment of available resources such as vehicles and shelters. Since the LEBMD-TW model is a multi-objective model, an epsilon-constraint method was therefore applied to solve the model.

The results of the LEBMD-TW model when applied to the case of Murrindindi Mill bushfire showed that the model was able to evacuate all late evacuees to four designated shelters. The evaluation of the model’s results showed that it was able to provide an optimal resolution for the evacuation when an unforeseen disruption occurs in the network. According to the proposed evacuation plan by the model, at least 14 busses and 10 vans were required to cover the same population under intense network disruption. The short-notice evacuation of late evacuees in the case of the Black Saturday bushfires could be executed using the existing resources. All late evacuees could be transferred from the region even when the main shelter shut down or the heavily used road disrupted. The model has proven to be reliable in generating optimal routings and evacuation solutions for problems involving complex evacuation scenarios. In each scenario, the model identified the shortest and safest routes to transfer late evacuees in bushfire- affected areas within the set time window, taking into account road accessibility and the available resources. The model has optimally assigned the available shelters to absorb all 1,100 late evacuees from the affected areas.

The town of Alexandra played a key strategic role in providing refuge to evacuees in all scenarios because of its geographic centrality. In addition, the Maroondah Highway was identified as the most heavily used arterial link, capable of connecting different parts of the region. The results showed that more than 59 per cent of short-notice Black Saturday evacuees could have been effectively transferred to key shelters via the Maroondah Highway due to high-capacity high-speed road connectivity. Further, the model assigned shelters on the basis of low risk routes even if the travel time were longer to minimise exposure to fire risk.

The simplicity of the LEBMD-TW model and the consideration aggregated objective functions are the main advantages of this model. The model results however indicated an increase in the number of assigned resources such as vehicles and shelters to maximise the covered population and route reliability. It means that the model sacrifices one objective to achieve optimal value for the next objective and may make the model less suitable or sub-optimal in resolving short-notice bushfire emergency evacuation. In the LEBMD-TW model, since each capacitated shelter is expected to serve the maximum number of late evacuees, it was assumed that each rescue vehicle always travels directly between its assembly point and the designated shelter, rather than travelling to additional places for further evacuee boarding. Therefore, the development of an aggregated vehicle routing model in the next step of this study addressed this problem objective.

### 7.2.2 Model II: CMDVRP-TW

The capability of vehicle routing programming with aggregated objective functions for providing an optimal short-notice bushfire evacuation model was assessed with the CMDVRP-TW model, which employed a heuristic approach. Similar to LEBMD-TW model, the objective function was to maximise the evacuation of the entire population in the region via safest routes. A heuristic approach was therefore developed to achieve the second objective as an optimal number of assigned vehicles. The approach decomposed the model to smaller problems by assignment of vehicles one by one while updating demands and capacities. In this model it was assumed that vehicles can travel between different nodes via different routes from all the affected assembly points to shelters to reduce the number of required vehicles. In other words, the total number of available vehicles in the entire network is not a hard constraint in the CMDVRP-TW model. A meta-heuristic approach was used to evaluate the effectiveness of the proposed heuristic model on 20 sets of various randomly generated evacuation problems.

The results of the CMDVRP-TW model implemented to the Murrindindi Mill bushfire case study showed that all stranded evacuees could be timely evacuated with only seven buses across four shelters.  The optimal output was also achieved when considering disruption in the main high-capacity shelter or a heavily used route. It showed that the CMDVRP-TW model was capable of generating efficient evacuation plans in different predefined bushfire disruption scenarios.

One major lacuna in E-DVRP was its inability to incorporate uncertainty in modelling parameters. In other words, it is difficult to frame the problem parameters as exact values in the deterministic models due to insufficient or unreliable historical bushfire data. Some parameters such as the number of evacuees, available time windows and shelter capacities, are often difficult to precisely determine. The assessment of the bushfire case studies CMDVRP-TW model showed that the model was quite sensitive to these data. The modelling showed that a slight change in the hard boundaries reflecting available clearance time and shelters' capacity can substantially change the evacuation plans and significantly increase the amount of resources required to perform the evacuation tasks. This limitation of the CMDVRP-TW approach necessitates considering the application of more sophisticated optimisation approaches which allow incorporating uncertainty in model parameters. The comparison of the results of the CMDVRP-TW and LEBMD-TW models led to the selection of the CMDVRP-TW model as the basis of further modelling.

### 7.2.3 Model III: P-CMDVRP-TW

The P-CMDVRP-TW model was developed to model short-notice bushfire emergency evacuation, which incorporated uncertainty in the key parameters. The objective function of this model aimed to maximise the number of evacuated late evacuees via the safest route, which is same as that of CMDVRP-TW. However, the solution approach is different whereby an interactive fuzzy approach was implemented in P-CMDVRP-TW. A heuristic algorithm was applied to derive the optimal number of required vehicles to solve the bushfire evacuee problem.

The results of the P-CMDVRP-TW model indicated that all evacuees could be safely transferred from the bushfire affected areas to four shelters by only six buses. Under disrupted scenarios, the results demonstrated that the model, when implemented to the 2009 Black Saturday Murrindindi Mill bushfire, would have enabled bushfire emergency services agencies to rescue all late evacuees within the clearance times with only seven rescue buses via utilising the safest routes. Applying the fuzziness in the key parameters in the P-CMDVRP-TW model showed the same amount of evacuees transferred to shelters with lesser number of vehicles via safer routes.

## *7.3 Meeting the research objectives*

This thesis aimed to develop optimisation models to enhance emergency response to short-notice bushfire evacuation under different disruption scenarios. To achieve this, two main objectives were set out and then formulated to *maximise the number of late evacuees from bushfire affected areas to safer places*, and *minimise the amount of allocated resources (shelters and vehicles) via the safest routes*. Four key research questions were developed and answered in this study.

Chapters 2 and 3 specifically addressed the first research question: *what optimisation approaches can be used to maximise short-notice evacuation under a given set of bushfire scenarios?* This question has been answered by comparing different approaches relating to the extent of emergency evacuation including the factors affecting the decisions, and the advantages and disadvantages of each approach. Three optimisation models were developed in Chapters 3 and 4 using different formulation methods. Since the models are complex and categorised as NP-hard problems, specific solution approaches were designed for each model to be able to solve the models with any problem size. The capability of models in generating evacuation plans under any bushfire scenario was then demonstrated under three plausible scenarios.

The second research question was addressed using mathematical optimisation modelling in Chapter 6. The second research question*, what is the optimum allocation of shelters required to maximise spatial coverage of late evacuees in bushfire affected area?* was answered by applying optimisation approaches to model to allocate shelters to maximise the evacuation of short-notice evacuees. The model, with or without disruptions, proved the effectiveness in the generation of evacuation plan that optimised the allocation of resources.

The third research question, *how can the most efficient routes (i.e. safest and shortest) be determined to transfer people from assembly points to designated shelters?* was addressed in Chapter 5. The developed models are capable in generating routes which are deemed most reliable in terms of their exposure to bushfire risk. Use of a fetch system resulted in the generation of most reliable routing plans (low risk routes). Although it increases the amount of resources required to maximise the coverage. While model 2 and 3 have similar routing structure with multi-destinations and pick-up points. This however resulted in routes which are at a higher bushfire risk due to reduced vehicles utilisation within the given time constraint.

The fourth and the final research question, *how can vehicle assignment and scheduling be optimised to maximise short notice evacuation within a specified time window?* was answered in Chapter 6. The first model LEBMD-TW utilised more vehicles in order to assign less risky roads. Once a vehicle assigned to one route, it starts to transfer evacuees in round trips in each time window. The second (CMDVRP-TW) and third model (P-CMDVRP-TW) used a vehicle routing structure that decreased the number of assigned vehicles, which in turn increased the risk.

The primary objective of this thesis, to develop optimisation models to enhance the emergency responses to short-notice bushfire emergency evacuation under different disruption scenarios, was therefore achieved.

## 7.4 Contribution of the study

The overall contribution of this thesis is the development of several short-notice bushfire evacuation models which are capable testing whether late evacuees could be transferred from assembly points to safe shelters through efficient, safe and quickest routes. The key contributions of this study are:

- This study developed an emergency evacuation framework that incorporated the complexity and uncertainty associated with short-notice evacuation into optimisation models. It constructed the evacuation framework as a complex system which consists of various inter-locking components such as shelters assignment, routing and scheduling of vehicles. The key to the study was to develop models that enable optimising the number of people transferred to safer places under uncertainty of bushfire. It conceptualised the framework as a holistic system with interactive and interdependent components. The framework was theorised on the basis of uncertainty theory within the multi-criteria decision process to generate tangible evacuation plans, capable of dynamically generating outputs to adapt to changing bushfire scenarios.
- The innovation in these optimisation models lies in their ability to simultaneously optimise complex capacitated vehicle routing across multi-pick-up assembly points and destinations under multiple-time windows via multiple routes. In addition, the application of these models to a large-scale regional study of the 2009 Black Saturday bushfires is also novel as most previous optimisation studies rely heavily on generated numerical examples.
- From a methodological perspective, this study has developed new methods and approaches to solve complex short-notice evacuation problem. In model I, the development of a mixed-integer multi-objective mathematical model (LEBMD-TW model) to allocate rescue resources to evacuate late evacuees to shelters is novel. In addition, a Pareto front non-dominant approach was applied to solve the LEBMD-TW model.
- In Model II, an innovative capacitated vehicle-routing optimisation problem with time windows was developed. The CMDVRP-TW model used in this

research integrated several VRP variants enabling emergency evacuation response options and transportation priorities to be quickly generated. This approach is innovative as it integrates four vehicle routing problem variants together to efficiently address the problem of this research by the allocation of a heuristic decomposition-based solution algorithm.

- In Model III, the possibilistic model (P-CMDVRP-TW) was developed by applying the possibilistic programming concepts to incorporate uncertainty in input parameters onto the CMDVRP-TW model. It is also synergistic with the paradigm of *if-then rules*, which are likely to be used for decision-making in the highly complex situations during evacuation operations. The P-CMDVRP-TW model incorporated real-world uncertainties such as population load, bushfire propagation, shelter capacity and variable time window and travel time. It is the first study in Australia that has developed optimisation models to handle the operational complexity of short-notice bushfire evacuation under a dynamic environment.
- In this study, a novel hierarchical exact heuristic algorithm as a solution approach was developed which decomposes the CMDVRP-TW model to minimise the number of assigned vehicles. Computational efficiency of the proposed algorithm was compared with an adjusted Meta-heuristic algorithm (GA) on a set of various random problem ensuring the practicability of the adopted algorithm. The results demonstrated the efficiency of the heuristic approach in generating better evacuation plans.

## 7.5 Planning Implications

The key purpose of this study was to generate tangible and pragmatic short-notice evacuation plans to enhance emergency response during bushfire. After a comprehensive investigation of a series of disasters, the Victorian Bushfires Royal Commission (2010) highlighted the need for amendment in the form of 67 recommendations in its final report to the Victorian Government in July 2010. In particular, the major focus *shifted toward the "necessity of urgent development and improvement of emergency evacuation components such as identification of neighbourhood safer places and potential shelters"* (Victorian bushfires royal commission final report, 2010, P 22,23). This research developed an operational framework for short-notice evacuation, which can simultaneously solve multiple operational tasks to enhance emergency response. This research provides evidence to demonstrate short-notice evacuation in an extreme bushfire conditions is still manageable through advanced operational planning and resource allocation. The analytics based insights drawn from various disruption scenarios could help emergency services agencies to develop emergency evacuation plans to mitigate the potential loss of lives during an emergency. Emergency evacuation plans represent three key components of short-notice evacuation..

### 7.5.1 Shelter allocation Plan

Applying the models developed in this research, emergency services agencies can optimally allocate shelters to evacuees in achieve any emergency evacuation planning objectives. An important consideration is to ascertain the minimum number of safe shelters in the vicinity of the bushfire-affected townships. The modelling applied in this research is capable of ascertaining the minimum number of safe shelters by assigning evacuees to be transferred within the restrictive time windows to efficiently serve bushfire affected areas. The models also show the important of back-up shelters during bushfires. Most evacuees could be transferred to safe shelters within the close vicinity (or centrality), but it increases the risk of over utilisation in case of a disruption. Having back-up shelters would decrease the risk to and increase the safety of evacuees. The dynamic assignment of the safest available routes to reach the allocated shelters, taking into consideration the pre-defined bushfire spread rate is of practical importance to emergency agencies. An assessment and risk-based ranking of evacuation routes and shelters provides further evidence to help develop a risk mitigation plan for emergency networks within a region.

### 7.5.2 Fleet assignment and routing

The fleet assignment and routing models were also shown to be useful for emergency services agencies, including local governments, in transit evacuation planning. The models practically demonstrate the functioning of the emergency transit system to ensure resources are optimally allocated while simultaneously evacuating all late evacuees via most reliable routes. Emergency planners can monitor vehicle utilisation and be able to assign different fleet (e.g. bus, van) to varying demand and time window constraint. The results from this research provide operational strategies for efficient transit operations. The models are capable as they can be readily adjusted to new management objectives to help simulate the potential outputs of changing allocation of resources. Risk mapping of reliable routes in a dynamic environment can be instantaneously mapped to show their vulnerability to potential bushfire disruptions.

### 7.5.3 Fleet scheduling plan

Scheduling of fleet can be stated as the timing and prioritising the utilisation of vehicles in order to minimise the total number of the required vehicles. Timely evacuation of late evacuees plays a predominant role in saving lives during a disaster. For example, the Rubicon and Taggerty townships are the first two townships that have been entirely evacuated under any bushfire scenario. However, emergency services agencies should evacuate people from townships at a higher risk that get evacuated as Narbethong, and Marysville. The modelling developed in this research generated a fleet scheduling plan whereby the timing, shelter and routes are assigned to fleet. The fleet schedules can be regenerated to changing management objectives to help plan future scenarios of resource allocation in term of establishing new shelters or assembly points.

## *7.6 Limitations and future research*

There are a number of limitations of the approach adopted in this study to model the short-notice evacuation. It is important to point out that evacuation plans and procedures are affected by additional factors apart from safety, potential infrastructure failures and tight time constraints. Some of these factors can be considered as potential input parameters in future research. Key limitations of this study are discussed as follows:

***Using stochastic modelling for the bushfire arrival time estimation***

In this research, the bushfire propagation rate and arrival time were extracted from historical 2009 Black Saturday bushfires data. An important and novel research extension for bushfire modelling on networks would be treated/considered to model the fire spread as a stochastic process, where the random variables underlying fire event moves among nodes of the network. In bushfire scenarios, insufficient historical data and the multiple potential patterns of propagation often make it difficult to frame the problem parameters as exact values. Time window and respective travel time, in this case, would be conceived as a random variable with a specific probability distribution function (e.g. exponential). Continuous first passage time models would be a suitable approach, which could be pursued in future research.

***Impacts of considering sub-networks***

The evacuation process, which is a focus of this research, is modelled as a relocation of the finite population within a regional network. The size of the evacuation network, the existence of many to small segments (trails, small streets) in particular, impacts the total evacuation process. The additional research in the ways of segmenting and clustering original networks into sub-networks, as well as application of parallel computing, would be valuable for the evacuation modelling. Development and usage of analytical approaches to estimate the population load on road segments is a promising research area for the adaptable evacuation planning research.

***Stochasticity in arrival and waiting time on pick up areas***

One of the key limitations of this research is that the evacuation route-planning problem is studied assuming a fixed population for the affected areas. In other words, it was assumed that all evacuees should be available at the start of the evacuation at time zero. However, during evacuations, different arrival times should be assigned to each group of evacuees to source nodes. Although this assumption is relaxed to some extent in this research by using possibilistic programming, considering stochastic arrival time for evacuees gathering in assembly points can be a valuable contribution for future research. On the other hand, considering stochastic arrival time for evacuees, rescue vehicles might not be available at the affected areas once one group arrives. An extension of the model to capture the time-dependent nature of evacuation and incorporate delays for evacuees to get to the pick-up locations and waiting times until the next vehicle has arrived will be highly valuable.

***Prioritise evacuation of special groups***

This research has not prioritised people at the assembly points, which is a major limitation of the adopted approach. It was assumed that all evacuees have the same level of priority for evacuation. However, besides time window priorities, there might be some people at pick up areas who are injured or burned and thus require urgent evacuation. One way to deal with this is to consider introducing “dummy” nodes and using them as origins for other classes/groups of evacuees. This approach is valid if the total load times into the evacuation network are comparable for these groups/classes of evacuees.

***Multimodal Evacuation***

This research considered methods in order to maximise evacuation of transit-dependent evacuees. However, in each disaster there are still several people who rely on their own vehicles to evacuate to the safer places. This part of evacuees increases the background traffic and cause network congestion that in turn affect the evacuation process. There are other modes of evacuation such as helicopters, ambulances, and personal automobiles, that could be integrated into a single evacuation framework. Future research may examine the possibility of integrating both auto-based and the transit-based aspects of evacuation. More analysis and modelling are needed to study the optimal mode shift to fully utilise the available transportation network.

***Application on other disasters***

Complexity in simulating people’s behaviour and bushfire propagation is also another limitation that may influence the effectiveness of the evacuation process. Other sources of ambiguity such as reducing road capacity that can happen due to flooding or avalanche along with the uncertainty of evacuee’s behaviour could be considered in future research. With appropriate model calibration and adjustment, this modelling approach could also be applied to other disasters such as flooding and cyclones, which are also widely prevalent in Australia and other countries.

***Graphical user interface***

This study has developed static representation of mapped data. The development of a visualised decision making prototype to generate reliable and more dynamic evacuation plans instantly and efficiently through online visualisation will add significant value for strategic and operational planners. This prototype would assist decision makers to operate an evacuation planning process more efficiently. This decision making tool will provide a user-friendly data entry system which can generate big data. This knowledge could be used to identify feasible evacuation routes, which can be easily and instantly adapted to changing bushfire scenarios.

## 7.7 Summary

This thesis developed three novel optimisation models aiming to maximise the number of late evacuees from bushfire affected areas to safer places within restricted time windows via the safest routes. The models developed here generated evacuation plans by computing solutions to shelter allocation, vehicle assignment and routing problems. The first model, LEBMD-TW, was a mixed-integer multi-objective optimisation model using a fetch system for evacuation of late evacuees. The Ɛ-constraint method was utilised as the solution approach. The LEBMD-TW is specifically designed for situations when there is no limitation on number of available vehicles. The results from LEBMD-TW show the feasibility to evacuate evacuees via most reliable routes.

The second model, capacitated multiple destination vehicle routing problem with time window (CMDVRP-TW), is a novel vehicle routing problem-model integrating several VRP variants. A heuristic solution approach was applied to tackle complex vehicle routing problem. The effectiveness of proposed heuristic algorithm was evaluated by comparison with a Meta-heuristic genetic algorithm using set of various computational experiments. The CMDVRP-TW model is the proper model for generation of bushfire plans based on a vehicle routing model along with time window consideration. The CMDVRP-TW model generated an evacuation plan which demonstrably minimised utilisation of vehicles.

The third Model, possibilistic capacitated multiple destination vehicle routing problem with time window (P-CMDVRP-TW), was presented as the key contribution of this study because of the novelty of integrating the CMDVRP-TW model with fuzzy set theory concepts. The P-CMDVRP-TW was shown to be suitable for bushfire evacuation when the emergency services agencies want to involve uncertainty in finding an evacuation plan. By the employment of the P-CMDVRP-TW model, which is an extended version of CMDVRP-TW model, the bushfire emergency services agencies could find the most optimal evacuation plan for improved resource utilisation under uncertainty in input parameters.

The models generated shortest and safest routes to transfer late evacuees from bushfire-affected areas within the set time windows, taking into account road accessibility and available resources. Overall, the LEBMD-TW model efficiently assigned available shelters to absorb all 1,100 late evacuees transferred from assembly points in the bushfire affected areas by a fleet of five buses and twelve vans. The CMDVRP-TW model suggests the evacuation of late evacuees by seven rescue vehicles in four shelters was feasible. A decrease in the number of assigned vehicles was shown to be possible, however, it increases the risk of transporting evacuees via high risk routes. The P-CMDVRP-TW model generated optimal routes and evacuation solutions under uncertainty and hard constraints. The research showed that it was possible to evacuate equal numbers of evacuees by using only six buses and four shelters under low disruption risk. The P-CMDVRP-TW model under disruption scenarios generated an evacuation plan to transfer all late evacuees with seven buses and four shelters.

The computed solutions developed in this research demonstrate that short-notice evacuation is manageable with advanced operational planning. The outputs of the evacuation models were shown to enhance the capacity of emergency services agencies to optimally allocate shelters, evaluate the reliability of assigned routes, and efficiently schedule rescue vehicles. The evacuation plans developed were shown to enable the emergency services agencies to identify most reliable routes and schedule vehicles to maximise the geographic coverage of the bushfire affected areas. Using these models, evacuees can be prioritised and scheduled according to risk and clearance time. In addition, taking into account the capacity of shelters, the solutions developed here demonstrated to which shelters evacuees should be sent to expedite the evacuation process. The modelling also provided solutions that identified the most used routes for evacuation by vehicles. The research demonstrated that application of advanced optimisation models can help emergency services agencies to generate plans to decrease the levels of disruption risk on the highly used routes and shelters under uncertainty in complex bushfire situations.

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Appendix

**Table A1** Network information

| | | Route 1 | | | | | Route 2 | | | | | Route 3 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| From | To | Road segments (links) | Travel time(min) | Distance (Km) | Disruption risk | Time windows(min) | Road segments (links) | Travel time(min) | Distance (Km) | Disruption risk | Time windows(min) | Road segments (links) | Travel time(min) | Distance (Km) | Disruption risk | Time windows(min) |
| Narbethong | Yea | L24-L26-L28-L29-L36 | 74 | 85 | 0.54 | 30 | L22-L30-L35-L36 | 112 | 63 | 0.5 | 30 | L20-L17-L17-L14-L41-L42 | 63 | 80 | 0.53 | 130 |
| | Alexandra | L20-L17-L16-L15 | 34 | 47 | 0.55 | 240 | L21-L19-L18-L17-L16-L14 | 48 | 52 | 0.52 | 195 | L20-L17-L12-L6-L13 | 41 | 50.7 | 0.55 | 130 |
| | Thornton | L20-L17-L12-L6 | 30 | 38 | 0.55 | 240 | L21-L19-L18-L17-L12-L6 | 40 | 45 | 0.52 | 195 | L21-L19-L11-L8-L7-L6 | 134 | 65.1 | 0.51 | 195 |
| | Eildon | L20-L17-L12-L6-L2 | 41 | 52 | 0.56 | 240 | L21-L19-L18-L17-L12-L6-L2 | 51 | 58 | 0.54 | 195 | L21-L10-L1 | 161 | 90.5 | 0.41 | 195 |
| | Yarra | L24-L25 | 36 | 35 | 0.48 | 270 | L24-L26-L28-L27 | 61 | 62 | 0.53 | 90 | L23-L7-L27 | 99 | 42.9 | 0.55 | 90 |
| Marysville | Yea | L19-L18-L17-L16-L14-L39-L40-L42 | 71 | 71 | 0.5 | 270 | L19-L18-L17-L16-L15-L41-L42 | 57 | 73 | 0.5 | 240 | L19-L18-L32-L33-L37 | 140 | 69.2 | 0.45 | 50 |
| | Alexandra | L19-L18-L17-L16-L15 | 34 | 42 | 0.5 | 270 | L19-L18-L17-L12-L6-L13 | 41 | 45 | 0.5 | 240 | L19-L11-L8-L7-L6-L13 | 135 | 65.5 | 0.5 | 240 |
| | Thornton | L19-L18-L17-L12-L6 | 30 | 33 | 0.49 | 270 | L19-L11-L8-L7-L6 | 124 | 53 | 0.49 | 240 | L19-L18-L17-L16-L14-L13 | 49 | 52.8 | 0.5 | 240 |
| | Eildon | L19-L18L17-L12-L6-L2 | 41 | 46 | 0.52 | 270 | L10-L1 | 19 | 17 | 0.41 | 280 | L19-L11-L8-L7-L6-L2 | 135 | 66.5 | 0.51 | 240 |
| | Yarra | L21-L24-L25 | 46 | 47 | 0.51 | 130 | L21-L24-L26-L28-L27 | 71 | 74 | 0.54 | 90 | L21-L23-L28-L27 | 106 | 58.8 | 0.58 | 90 |
| Buxton | Yea | L17-L16-L14-L39-L40-L42 | 59 | 59 | 0.5 | 300 | L16-L15-L41-L42 | 37 | 49 | 0.51 | 500 | L32-L33-L37 | 75 | 34.4 | 0.5 | 50 |
| | Alexandra | L17-L16-L15 | 22 | 30 | 0.51 | 500 | L17-L12-L6-L13 | 29 | 33 | 0.5 | 320 | L32-L38-L39 | 112 | 52.3 | 0.48 | 270 |
| | Thornton | L17-L12-L6 | 18 | 21 | 0.49 | 400 | L17-L16-L15-L13 | 33 | 42 | 0.51 | 30 | L18-L11-L8-L10-L6 | 127 | 62.3 | 0.47 | 270 |
| | Eildon | L17-L12-L6-L2 | 29 | 34 | 0.53 | 345 | L17-L12-L6-L2 | 29 | 34 | 0.53 | 320 | L17-L16-L14-L13-L2 | 48 | 54.4 | 0.53 | 320 |
| | Yarra | L20-L24-L25 | 48 | 53 | 0.53 | 240 | L19-L21-L24-l25 | 67 | 66 | 0.7 | 195 | L20-L23-L28-L27 | 108 | 64.1 | 0.6 | 90 |
| Taggerty | Yea | L16-L15-L41-L42 | 37 | 49 | 0.51 | 500 | L16-L14-L39-L40-L42 | 51 | 48 | 0.5 | 500 | L17-L32-L33-L37 | 136 | 69 | 0.45 | 50 |
| | Alexandra | L16-L15 | 14 | 18 | 0.52 | 500 | L16-L14 | 18 | 17 | 0.51 | 500 | L12-L6-L13 | 21 | 21.8 | 0.52 | 500 |
| | Thornton | L12-L6 | 10 | 9.4 | 0.5 | 400 | L16-L15-L13 | 25 | 31 | 0.52 | 500 | L16-L14-L13 | 29 | 29.4 | 0.52 | 500 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Eildon | L12-L6-L3 | 21 | 21 | 0.62 | 500 | L12-L6-L2 | 21 | 23 | 0.56 | 500 | L16-L15-L13-L2 | 36 | 43.9 | 0.55 | 500 |
| | Yarra | L17-L20-L24-L25 | 56 | 64 | 0.52 | 130 | L17-L20-L24-L27-L28-L27 | 78 | 92 | 0.55 | 90 | L16-L15-L42-L41-L36-L29-L27 | 78 | 107 | 0.53 | 90 |
| Cambarville | Yea | L10-L19-L18-L17-L16-L15-L41-L42 | 76 | 89 | 0.49 | 2;40 | L9-L8-L7-L12-L16-L15-L41-L42 | 163 | 101 | 0.48 | 300 | L10-L19-L18-L23-L33-L37 | 179 | 81.6 | 0.46 | 50 |
| | Alexandra | L10-L19-L18-L17-L16-L15 | 53 | 58 | 0.48 | 240 | L9-L8-L7-L6-L13 | 145 | 64 | 0.46 | 300 | L1-L2-L13 | 154 | 87.5 | 0.43 | 345 |
| | Thornton | L10-L19-L18-L17-L12-L6 | 49 | 50 | 0.46 | 240 | L9-L8-L7-L6 | 134 | 52 | 0.45 | 300 | L1-L2 | 143 | 75.1 | 0.41 | 345 |
| | Eildon | L10-L19-L18-L17-L12-L6-L2 | 60 | 63 | 0.49 | 240 | L1 | 132 | 62 | 0.37 | 345 | L9-L8-L3-L6-L3 | 146 | 71.6 | 0.53 | 300 |
| | Yarra | L10-L21-L24-L25 | 65 | 64 | 0.48 | 195 | L10-L21-L26-L28-L27 | 67 | 70 | 0.52 | 90 | L10-L21-L23-L28-L27 | 125 | 75.6 | 0.55 | 90 |
| Rubicon | Yea | L43-L4-L13-L13-L42 | 47 | 53 | 0.55 | 460 | L43-L4-L13-L39-L40-L42 | 59 | 58 | 0.54 | 460 | L43-L4-L6-L12-L16-L15-L39-L40-L42 | 72 | 73 | 0.53 | 460 |
| | Alexandra | L43-L4-L13 | 26 | 27 | 0.58 | 460 | L43-L4-L6-L12-L16-L15 | 39 | 42 | 0.55 | 460 | - | - | - | - | - |
| | Thornton | L43-L4 | 15 | 15 | 0.63 | 460 | - | - | - | - | - | - | - | - | - | - |
| | Eildon | L43-L4 | 147 | 76 | 0.42 | 345 | L43-L4-L2 | 26 | 28 | 0.61 | 460 | - | - | - | - | - |
| | Yarra | L43-L4-L6-L12-L17-L20-L24-L25 | 81 | 88 | 0.54 | 130 | L43-L5-L8-L11-L19-L21-24-L25 | 176 | 107 | 0.62 | 195 | L43-L4-L13-L41-L42-L36-L29-L27 | 90 | 116 | 0.55 | 90 |

**Table A2** Route segments data

| Code | Road name | Time window | Travel time (mins) | Distance (km) | Disruption risk % | Road capacity for | Road capacity for |
|---|---|---|---|---|---|---|---|
| L1 | Eildon-Warburton, Eildon Jamieson Rd | 345 | 132 | 61.7 | 0.37 | 2 | 3 |
| L2 | Goulburn Valley Hwy(B340) | 600 | 11 | 13.4 | 0.60 | 4 | 5 |
| L3 | Back Eildon Rd | 600 | 11 | 11.7 | 0.71 | 2 | 3 |
| L4 | Rubicon Rd | 460 | 12 | 10.7 | 0.64 | 3 | 4 |
| L5 | Blue Range Rd | 400 | 16 | 6.4 | 0.50 | 0 | 1 |
| L6 | Taggerty-Thornton Rd (C515) | 500 | 4 | 3 | 0.50 | 3 | 3.6 |
| L7 | Bulls Ln | 420 | 10 | 3.6 | 0.50 | 1 | 2 |
| L8 | Blue Range Rd | 340 | 52 | 19.9 | 0.50 | 1 | 1 |
| L9 | Lake Mountain-Royston River Rd | 300 | 68 | 25.3 | 0.39 | 0 | 1 |
| L10 | Marysville-Woods Point Rd(C512) | 280 | 19 | 16.8 | 0.41 | 3 | 4 |
| L11 | Mount Margaret Rd | 600 | 49 | 18.7 | 0.47 | 0 | 1 |
| L12 | Taggerty-Thornton Rd(C515) | 500 | 6 | 6.4 | 0.50 | 3 | 3.6 |
| L13 | Goulburn Valley Hwy(B340) | 600 | 11 | 12.4 | 0.53 | 4 | 5 |
| L14 | Breakaway Rd-Hoban Rd | 600 | 12 | 8.5 | 0.51 | 2 | 3 |
| L15 | Maroondah Hwy (B360) | 600 | 8 | 9.6 | 0.54 | 4 | 5 |
| L16 | Maroondah Hwy (B360) | 500 | 6 | 8.5 | 0.50 | 4 | 5 |
| L17 | Maroondah Hwy (B360) | 320 | 8 | 11.6 | 0.48 | 4 | 5 |
| L18 | Buxton-Marysville Rd (C508) | 270 | 3 | 3.9 | 0.50 | 3 | 4 |
| L19 | Buxton-Marysville Rd (C508) | 240 | 9 | 7.9 | 0.50 | 3 | 4 |
| L20 | Maroondah Hwy (B360) | 130 | 12 | 17.3 | 0.63 | 4 | 5 |
| L21 | Marysville Rd (C512) | 195 | 10 | 12 | 0.58 | 3 | 4 |
| L22 | Plantation Rd | 100 | 25 | 11.1 | 0.50 | 0 | 2 |
| L23 | Stony Creek | 300 | 75 | 22 | 0.57 | 0 | 2 |
| L24 | Maroondah Hwy (B360) | 270 | 23 | 21 | 0.49 | 4 | 5 |
| L25 | Healesville-Yarra Glen Rd (C726) | 270 | 13 | 14.2 | 0.47 | 3 | 4 |
| L26 | Healesville-Kinglake Rd (C724) | 190 | 17 | 16.1 | 0.48 | 3 | 4 |
| L27 | Melba Hwy(B300) | 90 | 14 | 17.3 | 0.54 | 4 | 5 |
| L28 | Healesville-Kinglake Rd (C724) | 220 | 7 | 7.5 | 0.73 | 3 | 4 |
| L29 | Melba Hwy(B300) | 240 | 13 | 18.8 | 0.63 | 4 | 5 |
| L30 | Murrindindi Rd | 60 | 66 | 24.8 | 0.51 | 2 | 3 |
| L31 | Black Range Rd | 90 | 70 | 26.3 | 0.51 | 1 | 2 |
| L32 | Cameron Rd | 270 | 55 | 26.4 | 0.50 | 1 | 2 |
| L33 | Simmonds Track | 135 | 20 | 8 | 0.50 | 1 | 2 |
| L34 | Myles Rd | 30 | 15 | 7.3 | 0.50 | 2 | 3 |
| L35 | Murrindindi Rd | 30 | 7 | 5.5 | 0.50 | 2 | 3 |
| L36 | Melba Hwy(B300) | 600 | 14 | 21.3 | 0.50 | 4 | 5 |
| L37 | Limestone-Ginter Rd | 50 | 53 | 23 | 0.36 | 2 | 2 |
| L38 | Scrubby-Black Range Rd | 300 | 45 | 17 | 0.44 | 1 | 2 |
| L39 | Whanregarwen Rd | 500 | 12 | 8.9 | 0.50 | 2 | 3 |
| L40 | Whanregarwen Rd | 500 | 11 | 8.1 | 0.50 | 2 | 3 |
| L41 | Goulburn Valley Hwy(B340) | 600 | 13 | 17.2 | 0.51 | 4 | 5 |
| L42 | Goulburn Valley Hwy(B340) | 600 | 10 | 13.8 | 0.50 | 4 | 5 |
| L43 | Rubicon Rd | 600 | 3 | 4 | 0.59 | 3 | 4 |

**Table A3** The Objective function and decision variables results are presented in the left column and the optimal routing transportation pattern results in the right columns.

| Number of available shelters | Optimal assignment of the resources | | From | To | Evacuees routing plan | | | Number of required vehicles | | | | Number of trips | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Route 1 | Route 2 | Route 3 | Vehicle type | Route 1 | Route 2 | Route 3 | Route 1 | Route 2 | Route 3 |
| Ω = 1 | Shelters | | Narbethong | Alexandra | 83 | 98 | 59 | Bus | 1 | 2 | 1 | 2 | 1 | 1 |
| | -Alexandra | | | | | | | Van | 1 | - | - | 6 | - | - |
| | Vehicles | | Marysville | Alexandra | 100 | 100 | 60 | Bus | 1 | 1 | 2 | 2 | 2 | 1 |
| | -Bus | 10 | | | | | | Van | - | 1 | 1 | - | 7 | 4 |
| | -Van | 11 | Buxton | Alexandra | 67 | 63 | - | Van | 1 | 2 | - | 4 | 2 | - |
| | Objective function value | | Taggerty | Alexandra | - | 70 | 100 | Van | - | 1 | 1 | - | 5 | 7 |
| | | 72.95 | Cambarville | Alexandra | 84 | - | 26 | Bus | 1 | - | 1 | 2 | - | 1 |
| | | | Rubicon | Alexandra | 90 | 100 | - | Van | 1 | 2 | - | 6 | 3 | - |
| Ω = 2 | Shelters | | Narbethong | Alexandra | 64 | 50 | - | Bus | 1 | 1 | - | 1 | 1 | - |
| | -Alexandra | | | Thornton | 26 | 100 | - | Bus | - | 1 | - | - | 2 | - |
| | -Thornton | | | | | | | Van | 1 | 2 | - | 2 | 3 | - |
| | Vehicles | | Marysville | Alexandra | 96 | 86 | - | Bus | 1 | 1 | - | 2 | 2 | - |
| | -Bus | 6 | | Thornton | 78 | - | - | Van | 2 | - | - | 3 | - | - |
| | -Van | 13 | Buxton | Alexandra | - | 48 | - | Van | - | 1 | - | - | 3 | - |
| | Objective function value | | | Thornton | 82 | - | - | Van | 1 | - | - | 5 | - | - |
| | | 59.95 | Taggerty | Alexandra | - | 70 | - | Van | - | 1 | - | - | 5 | - |
| | | | | Thornton | 100 | - | - | Van | 1 | - | - | 7 | - | - |
| | | | Cambarville | Alexandra | 19 | - | - | Van | 1 | - | - | 1 | - | - |
| | | | | Thornton | 91 | - | - | Bus | 1 | - | - | 2 | - | - |
| | | | Rubicon | Alexandra | 90 | 100 | - | Van | 1 | 2 | - | 6 | 3 | - |
| Ω = 3 | Shelters | | Narbethong | Alexandra | 71 | - | - | Bus | 1 | - | - | 2 | - | - |
| | -Alexandra | | | Thornton | 69 | 100 | - | Bus | 1 | 2 | - | 2 | 1 | - |
| | -Thornton | | Marysville | Alexandra | 60 | - | - | Van | 2 | - | - | 2 | - | - |
| | -Eildon | | | Thornton | 100 | - | - | Bus | 1 | - | - | 2 | - | - |
| | Vehicles | | | Eildon | - | 100 | - | Van | - | 2 | - | - | 3 | - |
| | -Bus | 7 | Buxton | Alexandra | 48 | - | - | Van | 1 | - | - | 3 | - | - |
| | -Van | 11 | | Thornton | 82 | - | - | Van | 1 | - | - | 5 | - | - |
| | Objective function value | | Taggerty | Alexandra | - | 89 | - | Van | - | 1 | - | - | 6 | - |
| | | 57.85 | | Thornton | 81 | - | - | Van | 1 | - | - | 5 | - | - |
| | | | Cambarville | Thornton | 68 | - | - | Bus | 1 | - | - | 2 | - | - |
| | | | | Eildon | - | 42 | - | Bus | - | 1 | - | - | 1 | - |
| | | | Rubicon | Alexandra | 90 | 100 | - | Van | 1 | 2 | - | 6 | 3 | - |
| Ω = 4 | Shelters | | Narbethong | Alexandra | 69 | - | - | Bus | 1 | - | - | 2 | - | - |
| | -Alexandra | | | Thornton | 81 | - | - | Bus | 1 | - | - | 2 | - | - |
| | -Thornton | | | Yarra | 90 | - | - | Bus | 1 | - | - | 1 | - | - |
| | -Eildon | | | | | | | Van | 1 | - | - | 3 | - | - |
| | -Yarra | | Marysville | Alexandra | 85 | - | - | Bus | 1 | - | - | 2 | - | - |
| | Vehicles | | | Thornton | 75 | - | - | Van | 2 | - | - | 5 | - | - |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | -Bus 5 | | Eildon | - | 100 | - | Van | - | 2 | - | - | 7 | - |
| | -Van 12 | Buxton | Alexandra | - | 55 | - | Van | - | 1 | - | - | 4 | - |
| | Objective function value | | Thornton | 75 | - | - | Van | 1 | - | - | 5 | - | - |
| | 52.8 | Taggerty | Alexandra | 70 | - | - | Van | 1 | - | - | 5 | - | - |
| | | | Thornton | 100 | - | - | Van | 1 | - | - | 7 | - | - |
| | | Cambarville | Alexandra | 20 | - | - | Van | 1 | - | - | 2 | - | - |
| | | | Thornton | 90 | - | - | Bus | 1 | - | - | 2 | - | - |
| | | Rubicon | Alexandra | 95 | - | - | Van | 1 | - | - | 7 | - | - |
| | | | Eildon | - | 95 | - | Van | - | 1 | - | - | 7 | - |
| | Shelters | Narbethong | Alexandra | 71 | - | - | Bus | 1 | - | - | 2 | - | - |
| | -Alexandra | | Thornton | 79 | - | - | Bus | 1 | - | - | 2 | - | - |
| | -Thornton | | Yarra | 90 | - | - | Bus | 1 | - | - | 2 | - | - |
| | -Eildon | | | | | | Van | 1 | - | - | 6 | - | - |
| | -Yarra | Marysville | Alexandra | 98 | - | - | Bus | 1 | - | - | 2 | - | - |
| | -Yea | | Thornton | 62 | - | - | Van | 2 | - | - | 2 | - | - |
| | Vehicles | | Eildon | - | 100 | - | Van | - | 2 | - | - | 3 | - |
| | -Bus 6 | Buxton | Alexandra | 48 | - | - | Van | 1 | - | - | 3 | - | - |
| $\Omega = 5$ | -Van 12 | | Thornton | 82 | - | - | Van | 1 | - | - | 5 | - | - |
| | Objective function value | Taggerty | Alexandra | - | 70 | - | Van | - | 1 | - | - | 5 | - |
| | 58.75 | | Thornton | 100 | - | - | Van | 1 | - | - | 7 | - | - |
| | | Cambarville | Alexandra | 9 | - | - | Van | 1 | - | - | 1 | - | - |
| | | | Thornton | 87 | - | - | Bus | 1 | - | - | 2 | - | - |
| | | | Eildon | - | 14 | - | Van | - | 1 | - | - | 1 | - |
| | | Rubicon | Yea | - | - | 100 | Bus | - | - | 1 | - | - | 2 |
| | | | Alexandra | - | 85 | - | Van | 1 | - | - | 6 | - | - |